UNVEILING PERCEPTIONS: AN EXPLORATION OF AI IN RECRUITMENT ACROSS AI EXPERT, APPLICANT AND RECRUITER PERSPECTIVES

Yasmin Elsaddik Valdivieso

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Abstract

Navigating the challenges of talent acquisition has prompted the adoption of e-recruitment practices, driven by technological advancements. While these innovations have addressed the persistent issue of finding quality talent, the rapid pace of technological change has ushered in transformative shifts in business processes. In the pursuit of competitiveness in the war for talent, companies are increasingly turning to the implementation of AI in e-recruitment. Despite discussion in academia and literature, the perceptions surrounding this adoption remain relatively unexplored.

This thesis employs a quantitative cross-sectional study conducted with AI experts, applicants, and recruiters in Canada. The empirical findings shed light on diverse approaches to AI implementation in the recruitment process, with some companies already integrating these technologies. Our methodology seeks comprehensive insights from relevant stakeholders. AI experts contribute technical knowledge and practical insights, offering crucial perspectives on the reliability of these programs. Applicants, as the primary audience for AI implementation, play a pivotal role, as their acceptance directly impacts an organization's ability to attract and retain talent. Lastly, recruiters, with their hands-on experience in the recruitment domain, provide valuable insights into the practical implications of AI tools.

Research reveals that AI can be effectively applied across all stages of the recruitment process, including description, outreach, screening, assessment, selection, and communication. In the description phase AI formulates targeted job ads, outreach involves identifying and engaging both active and passive candidates. The screening phase benefits from AI's ability to match candidates to job openings, scan resumes, and rank applicants. The assessment phase applies AI through video interviews, gamified simulations, and various tests. The selection phase enables the selection of candidates based on prior stages. Finally, in communication, AI facilitates coordination and engagement with applicants through scheduling tools and Chatbot interactions. Eight scenarios were presented to quantitatively analyze the perceptions of the stakeholders.

AI in the recruitment process was found to be fairer in the earlier stages than in the latter ones. Despite concerns regarding privacy, low fairness, and perceived creepiness, perceptions on organizational attractiveness remains positive throughout each scenario. This study caters to organizations uncertain about applicants’ perceptions of AI integration offering valuable insight into the receptiveness of candidates additionally it serves as a practical guide for organizations considering AI implementation. The findings show that participants expressed reservations about AI's emotional intelligence driven decisions. Privacy concerns emerge as a pervasive theme prompting crucial discussion on legal and regulatory compliance. In essence this thesis contributes to an examination of AI's impact on recruitment offering insights to stakeholders’ perceptions and encouraging organizations to navigate AI in recruitment.

Keywords: *Recruitment Process, AI in Recruitment Process, Perceptions towards AI, Perceptions of AI Experts, Perceptions of Applicants, Perceptions of Recruiters/*

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Preface

I, Yasmin Elsaddik Valdivieso, am the principal investigator for the presented thesis. I was responsible for co-conceptualizing the research design and leading the data generation analysis and write-up. Dr. Hussein Al Osman (thesis supervisor) co-conceptualized the research design including primary research questions methods and analysis. Dr. Hussein Al Osman reviewed, edited, and offered feedback throughout the entirety of the research process and shared academic resources to enhance the development of this thesis. Finally, prior to recruitment and data collection ethical approval was received from the university of Ottawa's research ethics board.8

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List of Acronyms

AGI	Artificial General Intelligence
AI	Artificial intelligence
ANI	Artificial Narrow Intelligence
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
ASI	Artificial Super Intelligence
ATS	Applicant Tracking Systems
HR	Human Resources
HRM	Human Resource Management
ML	Machine Learning
NLP	Natural Language Processing
OCR	Optical Character Recognition
PU	Perceived Usefulness
RL	Reinforcement Learning
SD	Standard Deviation
SHRM	Society for Human Resource Management
SL	Supervised Learning
TAM	Technology Acceptance Model
USL	Unsupervised Learning
WWW	World Wide Web

Chapter 1: Introduction

In this chapter, we will introduce the research topic, outline the areas of concern, discuss the subject choice, and discuss the background of the problem. We will also identify the research gap, guide the formulation of the research questions, and explain the study's purpose. Subsequently, in the following chapter, we will emphasize the significance of investigating this topic.

1.1 Problem Background

The advent of modern technology and the internet has brought about significant changes in traditional business methods. Today, competitors and affiliates are not confined to localized areas; instead, they operate on a global scale. Staying competitive in this global landscape is essential, necessitating the pursuit of a competitive advantage through the adoption of new technologies.

However, the timing of implementing these technologies is critical. Premature implementation, before users and consumers are ready, can have adverse effects. Conversely, delaying implementation may allow other entities to gain a competitive edge. Consequently, the growth of our economy is closely linked to the ongoing integration of automation, machine learning, and artificial intelligence.

The extent to which organizations can adapt and thrive in this digital era determines whether these global trends pose a threat or offer opportunities. The survival and prosperity of an organization in this era of economic growth hinges significantly on its ability to attract and retain top talent (McLennan, 2022). Employees are widely regarded as the cornerstone of an organization, and it is often said that "an organization is only as strong as its people" (Chrawshaw, 2014, p. 4).

In today's dynamic landscape, traditional recruitment approaches may no longer suffice to attract the most qualified and experienced talent. When we refer to "talent," we mean individuals who possess the skills and capabilities to excel in their roles and significantly contribute to the organization's growth (McLennan, 2022). The competitive battleground for talent is formidable, with the victors being those who adeptly harness technology, especially advanced recruitment, and selection tools. As Kane et al., (2017) aptly put it, "the capacity of companies to attract and retain talent is among the most critical digital threats the companies confront."

The evolution of recruitment methods over the past few decades reflects the changing times. In the early years of recruitment, Human Resources (HR) processes were labor-intensive and predominantly reliant on manual methods. This included reviewing paper-based resumes and conducting in-person interviews, among other manual tasks (Chapman & Gödöllei, 2017). Organizations would rely on newspapers and other print media to advertise job openings, requiring candidates to physically search job boards in pursuit of opportunities. However, this approach came with inherent limitations, often necessitating trade-offs between "richness" and "reach."

For instance, if an organization aimed to maximize the exposure for its job listings to reach as many potential candidates as possible, it had to contend with constraints on the amount of information that could be included in newspaper ads due to their high cost. This constrained the information richness of the job descriptions. Conversely, when companies sought to provide more comprehensive and detailed descriptions of job openings, they often limited the reach of these listings to a narrower, often local, audience, thus compromising "reach" (Black & van Esch, 2020). The need to address these limitations has driven the adoption of modern recruitment methods, commonly referred to as e-recruitment (Upadhyay & Khandelwal, 2018).

The phases of recruitment modernization, ranging from Digital Recruitment 1.0 to 3.0, have been classified by (Black & van Esch, 2020). During the 1990s and early 2000s, a significant transformation in the recruitment landscape began with the widespread adoption of email. This technological shift allowed recruiters to reach a larger pool of potential candidates, transitioning these platforms from mere communication tools to methods of candidate attraction (Chapman & Gödöllei, 2017). Simultaneously, the emergence of online job boards, such as Monster.com, revolutionized the approach to attracting candidates. Organizations were no longer forced to choose between expanding their reach and providing rich, detailed job listings. This transition marked the advent of Digital Recruitment 1.0, characterized by a shift towards online methods as opposed to traditional ones.

A decade later, Digital Recruitment 2.0 emerged, defined by two pivotal developments. First, job seekers gained the ability to find and apply for multiple job listings from a single platform, as exemplified by Indeed. This not only improved the applicant's experience but also allowed organizations to reach numerous candidates without having to create multiple job postings for the same role. The second major development was the rise of social networking platforms like LinkedIn, which enabled applicants to receive endorsements from their professional network while also affording recruiters a platform to post job opportunities and target prospective employees more effectively (Black & van Esch, 2020).

Digital Recruitment 3.0 was ushered in with the integration of Artificial Intelligence (AI). The need for this phase was a direct result of the previous two (Black & van Esch, 2020). While digital recruitment 2.0 expanded the geographical reach of job postings, it also generated an overwhelming volume of applications that proved time-consuming to sort through. Thus, the application of AI became indispensable for sorting and filtering resumes effectively. For instance, in 2017, Johnson & Johnson faced the daunting task of managing over one million applications for 28,000 positions (Klahre, 2017). Additionally, the pursuit of competitive advantage, fueled by the realization that superior talent underpins an organization's success, played a significant role in the development of Digital Recruitment 3.0 (Black & van Esch, 2020).

The adoption of AI in the recruitment process has marked a paradigm shift often referred to as "the new age of HR". AI technologies are driving this transformation, automating mundane and repetitive tasks, and fostering efficiency in the recruitment industry (Upadhyay & Khandelwal, 2018). AI, originally coined by John McCarthy, was founded on the premise of developing systems that exhibit human-like intelligence. This field encompasses a wide range of domains beyond computing and is interdisciplinary in nature. It aims to create systems capable of demonstrating human-like intelligence, including natural language processing, problem-solving, and planning (Tecuci, 2012).

In the context of this thesis, our focus is on AI-enabled hiring tools. These are defined as algorithm-driven solutions, software, applications, or tools designed to streamline or automate various tasks within the recruitment process.

Recruiting and retaining talent is paramount for Human Resource Management (HRM). The COVID-19 pandemic brought about a phenomenon often referred to as the "great resignation," with employees seeking new opportunities and organizational changes. In 2021, 84% of organizations reported labor shortages as a major challenge in HR (*State of the Workplace Study 2021-2022*, 2022). Remote work arrangements have gained prominence, with organizations finding them 1.5 to 2.5 times more effective than traditional in-person methods for recruiting talent. Furthermore, a quarter of organizations expressed their intentions to implement or expand the use of AI automation in their recruitment processes (*State of the Workplace Study 2021-2022*, 2022).

1.2 Research Gap

AI, in terms of recruitment, has evolved from being "nice to have" to "necessary", due to its improvement in efficiency (Black & van Esch, 2020). Which has led researchers to investigate AI implementation. Researchers have focused on the impact of AI on traditional recruitment methods (Black & van Esch, 2020; Johansson et al., 2019; Lundvall, 2022; Ween, 2020). They have found that AI-assisted recruitment permits companies to better organize their talent acquisition, optimize cost, and eliminate routine tasks. Will et al. (2022) investigated the integration of AI into the recruitment process while assessing whether AI is an adequate, better, or worse substitute for human recruiters. Some researchers have focused on AI attitudes in recruitment, specifically, from the perspectives of HR executives and recruiters (Boyd, 2022; Robinson, 2018).

Additionally, researchers have also focused on applicants' perspectives. With a focus on applicants' perceptions of the use of AI in recruitment in general such as to measure users perceived fairness (Hilliard et al., 2022), organizational perceptions and branding (Baratelli & Colleoni, 2022), usefulness (Black & van Esch, 2020; Horodyski, 2023a; Laurim et al., 2021), and even to determine perceived creepiness (Köchling et al., 2021; Langer et al., 2017).

While other researchers dived deeper into exploring the user perspective on AI-assisted recruitment at specific steps in the recruitment process. Laurim et al. (2021) focused on acceptance and rejection criteria of AI in the recruitment process, in terms of perceived usefulness, ease of use and lack of control in each step of the recruitment process (job advertisement, search, application, evaluation and selection) by performing 15 semi structured interviews, with 2 possible scenarios where AI can be used. While (Georgiou & Nikolaou, 2020) measured the level of attraction and openness of gamified assessment, by allowing applicants to experience video game interviews. Suen et al. (2019), conducted a similar study, but their focus was on the applicant's perspective regarding AI-based decision agents in video-interviews. A thesis from (Lisa et al., 2021) studied the attitudes of recruiters and applicants on AI in the recruitment process in Sweeden.

Most existing studies tend to focus solely on applicants, recruiters (HR professionals), or a combination of both. Current research also lacks a detailed exploration of how users perceive distinct stages of the recruitment process. This thesis aims to address this gap by providing insights into the perspectives of various user groups, including applicants, AI experts, and recruiters, regarding the integration of AI in specific stages of the recruitment process. We present a comprehensive analysis of the potential applications of AI at each step in the recruitment process, offering practical scenarios (e.g., employing chatbots in the communication step). By collecting survey responses, we aim to gain an understanding of how users perceive these scenarios. Furthermore, our research delves into the diverging viewpoints among applicants, recruiters, and AI experts. A particular focus on AI experts is driven by their extensive knowledge of AI capabilities, strengths, and limitations. We seek to determine whether expertise in AI influences users' perspectives.

1.3 Goals and Contribution

Our research focuses on the digital tools that have evolved to assist recruiters in optimizing the candidate selection and hiring process. Within this context, we aim to explore the multifaceted viewpoints of key stakeholders, namely recruiters, AI experts, and applicants. Our objective is to investigate how these stakeholders perceive the adoption of AI technologies in recruitment processes. By taking a unique and comprehensive approach, this research examines how AI can be effectively incorporated into each stage of the recruitment process. We provide an AI use case scenario in each step of the recruitment process, which offer a realistic and pragmatic application of AI allowing us to gain insight on user perspective (i.e., applicants, AI experts, and recruiters) on the application of AI in recruitment. This approach allows for a more nuanced assessment of AI's role and its implications for AI experts, applicants, and recruiters.

Our research goals are outlined as follows:

- Investigate and detail the current and potential future applications of AI across various stages of the recruitment process.
- Assess and compare the perceptions of applicants, AI experts, and recruiters on the use of AI in the recruitment process.
- Analyze the differences in perceptions among applicants, AI experts, and recruiters regarding AI's role in recruitment, and explore the causal relationships between these viewpoints.
- Explore how the integration of AI in recruitment stages impacts the perception of fairness among users, identifying best practices for equitable AI implementation.

1.4 Research Question

Considering the problem background and identified research gaps, our study investigates the following research questions:

Research question 1 (RQ1):

How is AI currently utilized at different stages of the recruitment process, and what are the potential applications of AI in these stages?

Research question 2 (RQ2):

What are the perceptions of applicants, AI experts, and recruiters regarding the use of AI at each stage of the recruitment process?

Research question 3 (RQ3):

Do the perceptions of applicants, AI experts, and recruiters differ with the integration of AI in each stage of the recruitment process?

Research question 4 (RQ4):

How does the potential integration of AI in various recruitment stages impact users' perception of fairness at each stage?

1.5 Delimitations

This study exclusively involves Canadian participants. Therefore, our findings may not be generalizable to other countries or cultures where perceptions of AI in recruitment might differ. Consequently, while the results provide valuable insights into the perceptions of Canadians on this subject, they should be interpreted with a recognition of these geographical and demographic boundaries.

1.6 Key Concepts

To mitigate potential sources of ambiguity, we provide definitions for key terms that we use throughout the thesis below.

Recruitment: This term refers to the process of searching, identifying, and attracting the best potential candidates to fill vacant positions in any organization (Anderson, 2021; Dhamija, 2012).

Recruiter: An individual employed internally or externally by an organization to find the best possible candidate for a vacancy in that organization. They are responsible for the entire recruitment process. The role includes assessing the qualifications, evaluating candidates' backgrounds, and communicating with them.

Traditional recruitment: This approach, often referred to as the "face to face" and paper-based recruitment, uses newspapers and in-person job boards to attract candidates for job positions (Chapman & Gödöllei, 2017).

E-recruitment: This approach uses communication technologies, such as websites and social media, to find and attract potential job applicants, to keep them interested in the organization during the selection processes, and to influence their job choice decisions (Chapman & Gödöllei, 2017).

AI: Is a technology that can perform tasks that typically require human intelligence

Applicant: A person with an interest in being evaluated for potential employment or promotion. (Robinson, 2018).

AI expert: Professionals who understand the various technologies and tools within the AI sector and play a pivotal role in the development of AI systems. They are responsible for developing, programming, and/or training algorithms that make up AI to emulate human-like cognitive functions. They are typically experts in software development, programming, data science and/or data engineering (Microsoft Team, 2023).

War for talent: The competition between companies to retain and recruit top talent (Ween, 2020)**.**

1.7 Assumptions

This study assumes that recruiters, as key players in the recruitment process, play a pivotal role in shaping the adoption of AI. It is also assumed that these recruiters, being actively involved in decision-making and strategic planning for recruitment, have a significant impact on the incorporation of AI supported technologies. Additionally, the research presupposes that AI experts possess comprehensive knowledge of emerging technologies, particularly in automation and AI implementation, along with a nuanced understanding of the associated implications, benefits, and pitfalls.

1.8 Thesis Organization

The rest of the thesis is organized as follows: Chapter 2 provides a literature review and outlines the theoretical framework pertinent to the research questions. Chapter 3 describes the methodology, encompassing both the collection and analysis of data. Chapter 4 presents and discusses the findings, detailing the survey responses and analyzing the results in relation to the methodological and theoretical concepts introduced earlier, while also considering the delimitations of our work. Finally, the thesis concludes with Chapter 5, where future research directions and limitations of the study are discussed.

Chapter 2: Literature Review

2.1 Human Resource Management

Human Resource Management (HRM) is “a comprehensive and coherent approach to the employment management and development of people” (Armstrong & Taylor, 2014, p. 1). It embodies a philosophy that focuses on the management of people within an organization. HRM is concerned with improving the organization and its people while incorporating an ethical dimension/perspective in its practices. It requires a set of policies and practices to be followed that are aligned with the overall company’s business strategy and goals (Johansson et al., 2019). It particularly considers the employees of the company and all aspects of their relationship with the organization, including the methods by which they are employed and managed. It is an approach to employee management that prioritizes the employee’s satisfaction to retain the workforce. By implementing diverse cultural, structural, and personnel strategies, it aims to enhance organizational performance and secure a competitive advantage (Storey, 2004). Some HRM practices include managing, training, recruiting, and retaining current and new employees by maintaining satisfaction levels (Dijkkamp, 2019; Johansson et al., 2019). The role of HRM within organizations has significantly evolved since its inception in the 1980s (Armstrong & Taylor, 2014). Initially perceived as a means of controlling employees, HRM has transitioned to a commitment-based approach, offering employees opportunities and encouragement for growth (Walton, 1985, p. 77). HRM is now considered a strategic method to gain and retain employees as they (i.e., employees) are considered the most important role asset of the company (Bas, 2012). Recruitment, a key component of HRM tasks and practices, encompasses advertising employment opportunities across various platforms (Holm, 2012).

2.2 Trends in the Recruitment and Selection Process

2.2.1 General Recruitment

The term recruitment refers to the “practices and activities carried on by the organization with the primary purpose of identifying and attracting potential employees” (Barber, 1998, p. 5). Other scholars believe recruitment comprises of not only attraction but selection as well (Armstrong & Taylor, 2014). Therefore, recruitment has two phases: attraction and selection (Ween, 2020). Attraction refers to the methods to draw in quality candidates (Armstrong & Taylor, 2014). On the other hand, selection refers to the comparison and sorting of candidates based on their suitability of the role in terms of their ability to execute the role successfully based on their experiences and education (Armstrong & Taylor, 2014, p. 195). There are many methods that can be applied to achieve proper recruitment and selection. However, the success of these methods largely depends on receiving suitable applications, as well as considerations of time and budget constraints. The employees of a company are the most valuable assets. They are employed and recruited by HR. According to the Society for Human Resource Management (SHRM), the average cost-per-hire is $4700 USD (Navarra, 2022). Therefore, it is important to have qualified HR employees to recruit qualified candidates in a timely manner. There are two types of recruitment: traditional and non-traditional recruitment. Figure 2.1 depicts the different branches of recruitment and their subcategories.

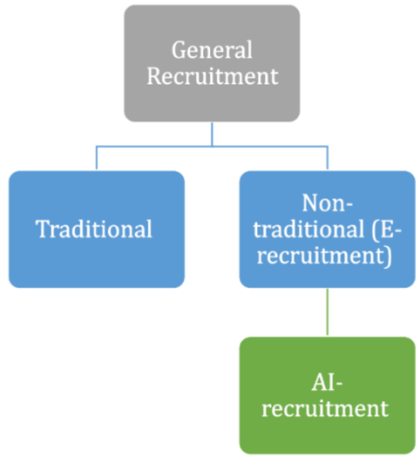

Figure 2.1. The different branches of recruitment.

2.2.2 Traditional Recruitment Transition to Non-traditional

Traditional recruitment is generally the "face to face" method. It refers to the time when recruitment required paper-based methods for job posting such as newspapers and job boards. There were local areas for attracting and hiring candidates such as designated general arenas (Chapman & Gödöllei, 2017). Generally traditional recruitment is performed by the HR department within the company. The HR team would use existing networks or internal recruitment methods to hire for vacancies. Though traditional recruitment is successful in hiring new employees, it has significant inefficiencies. The cost and hiring time are long and the geographical coverage for potential hires is low (I. Lee, 2005). In fact, the average hiring cycle is 90 days (I. Lee, 2005, p. 58).

According to a recruiter interviewed by Lisa et al. (2021), "the total recruitment is about 9 to 14 weeks (about 3 months) from start to when everything is ready" (p.44). The traditional recruitment process has advanced and updated to mold the changes and effects of internet and technology (Dhamija, 2012). The process of digitalizing recruitment is called online recruitment whose synonym is e-recruitment. E-recruitment is considered as "one of the most successful e-commerce applications" (I. Lee, 2005, p. 57). Its benefits include reaching a larger pool of job applicants, being time efficient, and cost effective. It has been available since the late 1990s (I. Lee, 2005) and has become a trend in automating recruitment processes, and other HRM tasks (Dhamija, 2012). It enables applicants to submit their resumes via an electronic format, thus allowing organizations to efficiently manage applications. This method is considered one of the most popular non-traditional recruitment methods (Dhamija, 2012) and is known for being faster, more cost-effective, and efficient compared to traditional recruitment processes (Johansson et al., 2019; Kapse et al., 2012). However, traditional recruitment provides a valuable component: the human touch. Kapse et al. (2012) suggests that blending traditional recruitment with modern electronic methods may provide the best approach for finding ideal candidates. Acikgoz et al. (2020) believes that there are two models to recruitment: one from the perspective of the organization's point of view and the other from the job-seeker's point of view. For this thesis, both perspectives will be considered.

2.2.3 E-recruitment

E-recruitment is identified as of the fastest-growing recruitment techniques by Lee (2005). Originally referred to as "recruitment of candidates on the internet" (Holm, 2012, p. 254), e-recruitment has evolved into the "usage of online technology to attract candidates and help in the recruitment process" (Kapse et al., 2012, p. 82). A more comprehensive definition of e-recruitment is provided by Holm (2012), who describes it as "the organization of recruitment process and activities, which, by means of technology and human agents, facilitate time- and space-independent collaboration and interaction in order to identify, attract, and influence competent candidates".

E-recruitment proves beneficial as it increases the probability of making a good hire for a job opening, given the larger and more diverse pool of candidates. Introduced in the mid-1990s, e-recruitment was initially hailed as a "recruiting revolution" for its capacity to connect employers with prospective employees (Dhamija, 2012).

Lee (2005, p. 59) outlines nine key steps in the e-recruiting process: (1) identification of hiring needs, (2) submission of job requisition, (3) approval of job recognition via a job database, (4) job listing on the internet, (5) submission of applications by applicants directly into the applicant database, (6) online search in the applicant database for candidate selection, (7) online evaluation of resume applications, (8) interviewing by recruiters and hiring managers, (9) online pre-employment screening, and (10) job offer and employment contract. The pivotal step in the e-recruiting process is the posting of a job on an online board. Examples of these boards include hiring companies' websites, third-party sites like LinkedIn or Indeed, and social media platforms. Notably, this step is advantageous for applicants, as a 2019 online survey by Jobvite revealed that employer career sites were more favorable and attractive for candidates when applying for jobs. For employers, the ease of access is advantageous, as it allows for easy editing of the advertisement whenever and wherever there is internet availability, compared to physical job postings that may incur high costs and necessitate reissuing of the data (Ween, 2020). Lee (2005) conducted a comprehensive study analyzing the e-recruitment practices of Fortune 100 companies. From his research, he proposed a five-stage evolution model of e-recruitment, based on technological and automation advancements. The stages are outlined as follows:

1. Stage 1 (Information Delivery E-Recruiting System): In this initial stage, job posting information is primarily posted on company websites or third-party sites.
2. Stage 2 (Search Engine System): Building upon Stage 1, Stage 2 introduces an interactive search engine. This feature enables applicants and recruiters to sort information regarding available job openings efficiently. Specific search parameters include, but are not limited to, keyword searches, workplace location, and job category.
3. Stage 3 (Enhanced Search Engine System): A more advanced version of Stage 2, Stage 3 goes beyond interactive searches. It involves sending information on job postings and CVs to recruiters and job seekers based on predefined criteria and search history.

4. Stage 4 (Decision Support): This stage aids recruiters in refining their selection of applicants by guiding them through an online self-assessment test before applying. The assessment evaluates strengths and weaknesses, interpersonal skills, education level, etc. For candidates, these self-assessment tools offer insights into areas needing improvement. The system analyzes responses to pre-screening questionnaires, ranking candidates based on suitability for the job opening.
5. Stage 5 (Holistic): The final stage represents the e-recruitment system as a comprehensive entity, integrating normal human resource tasks with the recruiting process. This integration creates a competitive advantage, fostering a two-way, long-term relationship between employers and potential employees.

2.3 Comparison of Traditional and Modern recruitment methods

2.3.1 Steps in General Recruitment

The recruitment process involves multiple steps, each of which can be further broken down into sub-steps. A detailed description of these steps is provided in Table 2.1.

Table 2.1 Stages of recruitment and employee selection process. Adapted from (Holm, 2012, p. 244; Saalasti, 2017, p. 6)

Step	Task	Description
1	Define job requirements and identify hiring needs	• Develop a role profile that defines proper job descriptions and lays out requirements and job specifications including abilities, skills, and education **(Armstrong & Taylor, 2014, p. 192).** • Identify the type of candidate the vacant role requires.
2	Attract applicants	• Select a source for recruitment and announce vacancies, e.g., newspaper, Indeed, LinkedIn, social networking sites.
3	Receive, sort, and screen applications	• Receive and sort incoming applications. • Organize and file applications. • Sift through CVs and compare applicants.
4	Process candidates	• Interview candidates, possibly multiple times by different interviewers. • Test candidates' abilities such as aptitude tests. • Assess the compatibility of the candidate's personality and characteristics with the company's culture. • Validate candidates' education and experience by contacting references.
5	Communicate with applicants	• Inform candidates' that have not been selected for the next stage and provide feedback (Abbas et al., 2019, p. 6). • Propose a job offer.

Traditional recruitment, as outlined by Holm (2012), is characterized as a linear process, while e-recruitment, according to Lee (2011, p. 233), operates on a continuous model, enabling simultaneous recruiting and selection. The recruitment process involves distinct steps, which are elaborated upon in Table 2.1. The initial phase centers around establishing recruitment objectives, understanding the specific position to be filled, and analyzing the ideal candidate profile. This includes crafting a comprehensive role description and specifying required skills, educational background, language proficiency, and experience. Subsequently, the development and attraction phase, as discussed by Johansson et al. (2019, p. 12), requires organizations to make decisions on sources and methods for attracting applicants, alongside creating targeted messages. Budget constraints are factored into this planning. The subsequent recruitment activities involve receiving, screening, sorting, and filtering incoming applications (Holm, 2012, p. 243), resulting in the creation of a shortlist of potential candidates. The fourth step revolves around processing candidates, which includes interviews, skill assessments, and credential validations through reference checks. The final recruitment result stage connects to the initial objectives, involving contacting applicants, presenting job proposals to successful candidates, and communicating rejections when needed (Johansson et al., 2019, p. 12).

2.3.2 Steps in E-Recruitment

E-recruitment has revolutionized the process of job issuance and stands as the predominant method for employee recruitment (Kapse et al., 2012). The initial step in e-recruitment, mirroring traditional approaches, involves defining job vacancies and identifying the current organizational needs. The subsequent phase is dedicated to attracting applicants, with considerations for internal and external recruitment methods (Kapse et al., 2012). Figure 2.2 provides examples of both internal and external recruiting methods. Attracting applicants is achieved through online advertising on the World Wide Web (WWW). Two primary options are available for companies, with the choice influenced by the sophistication level of technology used (Mohammed, 2019, p. 47). Option a) entails utilizing online job portals such as LinkedIn and Indeed, where job descriptions are posted, and the portal matches suitable resumes from applicants. This method streamlines the application process for candidates, saving them time compared to traditional methods (D'Silva, 2020). Option b) involves posting job listings directly on the company website, allowing passive job seekers to submit their resumes directly to the organization's database. This method facilitates a direct understanding of the job role and application submission without intermediaries, a practice favored by top companies (D'Silva, 2020). To enhance visibility, companies can leverage social media and other networking sites for advertising and link-sharing. The choice between the two options depends on factors such as the organization's size, budget constraints, and specific requirements. Ultimately, companies must ensure that their websites are attractive and user-friendly to encourage seamless applicant submissions.

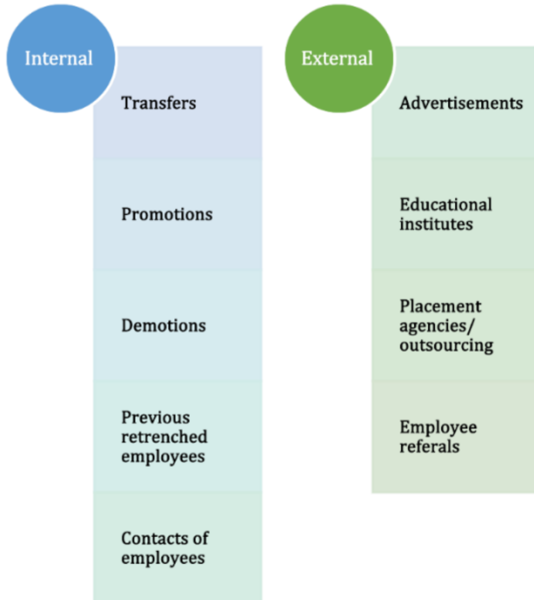

Figure 2.2 Sources of recruitment. Internal recruitment methods and external recruitment methods. Based on information retrieved from (Kapse et al., 2012; Sills, 2014)

The third stage involves the management and sorting of candidates once their applications are submitted. HR recruiters undertake the crucial task of reviewing applicants' qualifications in relation to the job description, a process made notably more efficient with the use of resume scanners (D'Silva, 2020). These scanners, also known as Applicant Tracking Systems (ATS), employ pre-defined criteria and keyword searches within resumes to screen and categorize applicants (Indeed Editorial team, 2021). ATS systems assist hiring managers in streamlining the candidate pool by eliminating unqualified individuals based on preset conditions, such as educational background, competencies, years of experience, former employers, and skills (Oracle Team, 2022). The subsequent step involves conducting online interviews, a process facilitated by the integration of ATS with hiring staff calendars (Outlook, Gmail) for efficient scheduling. Two-way online video streaming platforms like Google Meet, Facetime, and Zoom are commonly employed for interviews, where HR recruiters lead the conversation, and candidates respond. Coordinating a suitable time and date remains a challenge, often requiring coordination between applicants and short-listed recruiters through email (D'Silva, 2020). The final phase centers on closing the deal. Once the final candidate is selected and contacted, other candidates are informed of the decision, utilizing automated systems, chatbots, or simpler methods such as employee-conducted email rejections. Rejected candidates may receive constructive feedback on the reasons for their non-selection. Conversely, selected candidates may be scheduled for a final conversation through online platforms like Zoom or Skype. A general overview of the different recruitment styles is shown in Figure 2.3.

Figure 2.3 Comparison of different recruitment styles and their steps. (traditional, E, and AI), and compares them to one another.

2.4 Application of AI in E-Recruitment

2.4.1 Defining AI

AI is the science of designing systems to emulate human thinking, encompassing their ability to learn, remember, make decisions, and execute tasks (Chen, 2022). Coined by John McCarthy in 1956, the term initially surfaced in a proposal focused on the "posibilities of intelligent machine implementation" (Chen, 2022). Another definition characterizes AI as an "ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019, p. 15). AI relates to 4 main dimensions: "thinking humanly, acting humanly, thinking rationally, and acting rationally" (Russell, 2003, p. 3), fundamentally aiming to think and act in a manner akin to humans. The concept of "intelligence" within artificial intelligence remains challenging to define, with interpretations varying based on conditions and environments (Jarrahi, 2018). Intelligence, informally understood, encompasses the ability to acquire knowledge, retrieve information, or adapt to an environment (Legg & Hutter, 2007). AI algorithms learn user interactions and predict online behavior, with applications like Siri utilizing voice recognition for user interaction. Algorithms use extensive data inputs and outputs to recognize patterns and "learn," enabling machines to autonomously make recommendations or decisions (Helm et al., 2020, p. 69).

Machine Learning (ML), a subset of AI, refers to algorithms that can learn and refine themselves without explicit programming (Heymans, 2021). Linked with terms like "learning" and "human intelligence," ML involves acquiring the capability to learn and enhance analytical methods through computational algorithms (Helm et al., 2020). The machine, with practice and algorithmic repetition, can take an input and predict an output. Accuracy is assessed by comparing predicted outputs to known outcomes in labeled datasets. The algorithm can be iteratively adjusted to improve its performance on a particular task (Haeberle et al., 2019; IBM Cloud Education, 2020a).

Supervised Learning (SL) is a method used in ML, often for predictions or data categorization (IBM Cloud Education, 2020a). In AI recruitment, SL is applied in identifying candidates, resembling a search engine function, as seen in stage 2 of e-recruitment (I. Lee, 2005; Ween, 2020). Unsupervised Learning (USL) employs machine learning algorithms to analyze and cluster unlabeled datasets, identifying patterns without human intervention (IBM Cloud Education, 2020b; Ween, 2020). In AI recruitment, USL is used in stage 3 of e-recruitment for search and recommendation engines, providing information based on predefined criteria (I. Lee, 2005; Ween, 2020). Reinforcement Learning (RL) combines elements of SL and USL, where machines learn to achieve positive outcomes without explicit instructions, receiving positive reinforcement for desirable outcomes (Heymans, 2021; Ween, 2020).

Deep learning, a subset of machine learning, employs multi-layered Artificial Neural Networks (ANNs) to mimic human behavior (IBM Cloud Education, 2020a). These networks consist of interconnected nodes, or artificial neurons, where the number of layers determines the network's depth (Kavlakoglu, 2020). In deep learning, each node sends signals to others, with varying weights impacting the subsequent layers' processing. This structure allows for complex pattern recognition and decision-making capabilities, similar to human neural activity. ANNs have been especially useful for applications that involve image classification, speech, and language recognition. They have been instrumental in everyday applications such as facial recognition in Google Photos and voice recognition in digital assistants like Siri and Cortana (Reyes, 2022). Deep learning also plays a pivotal role in e-recruitment, particularly at the decision support stage, by helping hiring managers make informed choices (I. Lee, 2005). The overall subsets of AI are shown in Figure 2.4.

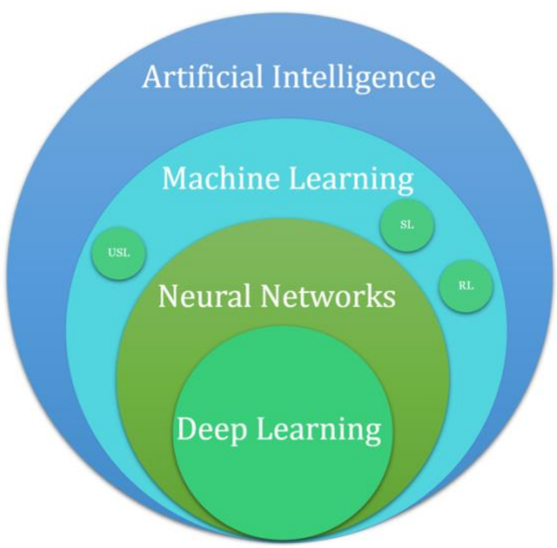

Figure 2.4. Subsets of Artificial Intelligence include machine learning and its divisions, neural networks, and deep learning. Adapted from (Kavlakoglu, 2020; Srivastav, 2020)

2.4.2 AI Categories

Broadly, we can define three categories of AI: Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Super Intelligence (ASI). ANI, often associated with stage 1 or machine learning, excels in specific tasks, or solves problems. It is the only category currently produced and can perform facial recognition, voice recognition, and automated driving (Srivastav, 2020). ANI utilizes Natural Language Processing (NLP) for interaction between computers and humans, as seen in applications like voice-to-text messaging systems, spell checkers, and chatbots that comprehend human natural language (Escott, 2017; Wonderflow, 2018). In contrast, AGI and ASI are considered more advanced or "stronger" forms of AI (Kavlakoglu, 2020). AGI, akin to stage 2 or machine intelligence, possesses capabilities comparable to humans, imitating human intelligence with the ability to learn, adapt, and exhibit human behaviors (Chen, 2022; Srivastav, 2020). AGI would essentially mirror a human being in its cognitive abilities. ASI, representing stage 3 or machine consciousness, goes beyond human intelligence, demonstrating superior capabilities such as enhanced memory capacity and retrieval (Chen, 2022; Srivastav, 2020). In this stage, machines would attain full consciousness (Escott, 2017). However, for the purpose of this research and in line with current discussions, the focus will be on ANI. ANI encompasses facial recognition software, social network monitoring tools, recommendation services, virtual assistants, and more (Escott, 2017).

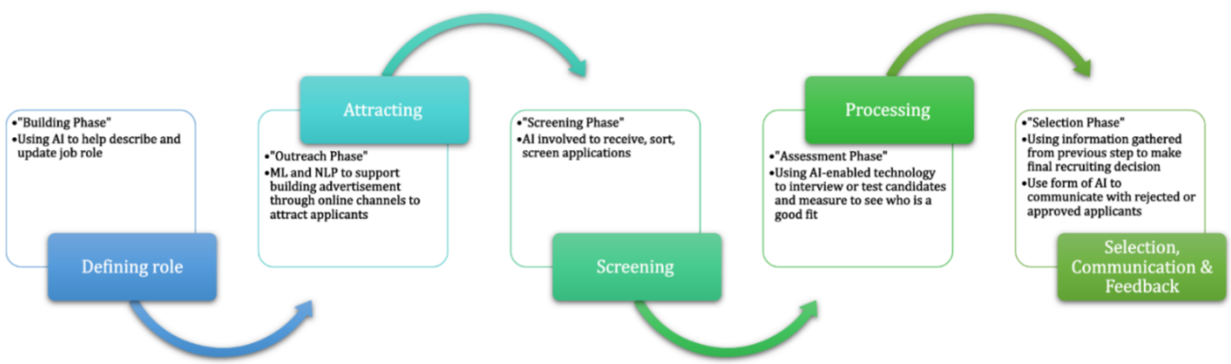

Figure 2.5 Application of e-recruitment with AI implementation, adapted from information sourced by (Chen, 2022; Holm, 2012; Laurim et al., 2021; Lisa et al., 2021)

2.4.3 AI-Recruitment

Recruitment encompasses various branches, with traditional and e-recruitment being prominent categories. AI-recruitment is positioned within the e-recruitment domain, as illustrated in Figure 2.1. This entails the utilization of AI, coupled with ML technology, to make algorithmic decisions throughout the recruitment and selection process, marking it as a pivotal element in the evolution of the recruitment industry (Upadhyay & Khandelwal, 2018, p. 255). AI tools can be integrated into the five primary stages of recruitment, namely job description, outreach/sourcing, screening, assessment, and selection, as depicted in Figures 2.3 and 2.5. The involvement of AI in these stages varies among researchers, with some recognizing three stages, including outreach, screening, and assessment (Baratelli & Colleoni, 2022), while others identify six stages: job advertisements, job search, application, selection, assessment, and coordination (Chen, 2022). For this thesis, we will streamline the stages to five, as illustrated in Figure 2.5. Chapter 1 introduced RQ1: “How is AI currently utilized at different stages of the recruitment process, and what are the potential applications of AI in these stages?” This research investigates the application and utilization of AI, examining its integration throughout the selection process, from the initial stage to the final stage. Figure 2.5 visually maps out each step of the AI recruitment process, providing an overview of the journey. Our research reveals that AI can play a pivotal role in every step of the recruitment process, from crafting job descriptions, attracting applicants, screening candidates, processing applications, making selections, and handling communication. This is made possible through tools like ATS, Chatbot interactions, gamified assessments, and avatar interviews.

The following describes how AI can be implemented at various stages of the recruitment process (section 2.4.4 to 2.4.8). However, not all companies adopt these innovations to the same extent. Some continue to depend on currently established e-recruitment methods, while others persist with traditional approaches.

2.4.4 Job Description

Job descriptions or ads can be created, edited, and updated with the help of AI. The integration of AI in this process involves analyzing and comparing previous job descriptions to the current tasks and responsibilities (Chen, 2022; Laurim et al., 2021). Tone meters can improve inclusiveness by adjusting the tone of the ad to attract more men or women (Hunkenschroer & Luetge, 2022). This strategy helps customize, or even decrease biases by making ads gender neutral. Companies like Textio, use text-mining techniques, leverage AI to adjust the wording of job descriptions in advertisements dynamically and predict attractiveness of job listings. The software scans the job ads for key words to help it improve its performance and monitors the impact of these listings on the number of applicants and their demographics, offering valuable insights to companies seeking to enhance their outreach and improve their hiring strategies (Black & van Esch, 2020; Hunkenschroer & Luetge, 2022). Notably, Johnson & Johnson utilized Textio's platform, resulting in a 9% improvement in female applications. This exemplifies the tangible impact of AI in optimizing the language and content of job descriptions to attract diverse and qualified candidates.

2.4.5 Outreach

The outreach phase is where AI can be implemented to help identify candidates and effectively promote job opportunities to encourage applications (Baratelli & Colleoni, 2022). The objective is to increase the number of incoming applications, thereby enhancing the chances of selecting the most suitable candidate (Chen, 2022). AI achieves this by tailoring presentation methods, such as banner ads, emails, or text messages, to different target candidates, strategically promoting the role and persuading candidates to apply (Baratelli & Colleoni, 2022, p. 49). These AI tools determine which aspects of the company to highlight and select the optimal method to engage with candidates (Chen, 2022). ATS, a recruitment tracking tool, often incorporates AI and ML to create and identify the 'ideal candidate,' offering valuable insights into candidate behavior and enabling targeted outreach (Oracle Team, 2022). These tools even have the ability to make predictions about candidates’ future job performance (Bogen, 2019; Hunkenschroer & Luetge, 2022). ATS can be utilized for job postings across various channels, including social media, slack, social networking sites, job boards, and company websites (Oracle Team, 2022). Platforms like Hireology assist HR teams in hiring and management by identifying and tracking candidates through search engines, social media, and job boards (Hireology Team, 2022).

The primary goal for companies during the hiring process is to identify the most suitable candidate for a role, a task made less challenging with the assistance of AI (Hunkenschroer & Luetge, 2022). Advertisements must strike a balance, being broad enough to reach a wide audience while being specific enough to attract the right candidates. AI is particularly useful in engaging passive candidates—individuals not actively seeking new opportunities but open to compelling offers. The number of passive candidates often surpasses that of active candidates, making them a valuable talent pool (Black & van Esch, 2020). Many companies possess a pool of rejected candidates, which AI-enabled tools can reevaluate and potentially match with new available positions swiftly (Black & van Esch, 2020). Loreal's adoption of AI, particularly the use of the chatbot named Mya, resulted in receiving 2 million applications for 5000 roles, showcasing the effectiveness of AI in attracting and identifying potential applicants (Sharma, 2018).

In the outreach stage, AI tools benefit both recruiters and job seekers. For job seekers, these tools facilitate the identification of suitable opportunities based on preferences such as geographical location, demographic data, job skills, and employer environment (Chen, 2022). Automation aids applicants in filling in information on job listings based on previous data and uploaded CVs, with programs assisting in automatically filling online applications (Laurim et al., 2021; Swapna & Arpana, 2021). Additionally, digital helpers, employing NLP and ML, can assist applicants by providing research support, grammar correction, tone adjustment, and increased processing speed (Barker, 2022; Hedge, 2022). AI also enhances job board searches, guiding applicants through a smooth application process.

2.4.6 Screening

Once potential applicants are identified, the screening phase becomes instrumental in filtering, sorting, and evaluating applications and CVs. AI-enabled tools can help in refining the pool of candidates by scanning incoming CVs, identifying key terms, and assessing prerequisites to highlight the top matching candidates. This screening process aids companies in identifying high-quality candidates that best fit the role, with AI contributing to significant lead time reductions ranging from 60-90% (Baratelli & Colleoni, 2022, p. 49). AI tools, such as Ideal, an automated talent scanner, can rapidly screen thousands of applicants in real-time, shortlisting and identifying ideal candidates, leading to a substantial decline in hiring time, as reported by Hilton Hotels & Resorts and their 88% reduction in time-to-hire (Ideal Team, 2022; McLaren, 2018). Another noteworthy example is Loreal, which experienced a significant reduction in screening time, from an average of 45 minutes to just 4 minutes, by employing AI-enabled tools in recruitment (Sharma, 2018). The implementation of such tools in the hiring process not only expedites the overall process for companies but also presents a competitive advantage. For candidates, the reduced waiting time for responses and job offers makes employers using AI-enabled tools more attractive. ATS technology is a significant support in the screening stage of recruitment, allowing for quick application sorting and minimizing errors that might occur in manual resume screening (D'Silva, 2020). AI tools like "resume scorers" and "Optical Character Recognition (OCR)" are employed to efficiently screen through resumes, contributing to the speed and accuracy of the hiring process (D'Silva, 2020). The benefits of these technologies are demonstrated in various cases, showcasing improved efficiency and decreased time-to-hire for organizations employing AI in their screening processes.

2.4.7 Assessment

The screening phase helps eliminate unsuccessful applicants, with 50% to 30% remaining (Black & van Esch, 2020). ATS helps with sorting of pre-approved candidates and can be facilitated by online screening tests which can consist of qualitative or quantitative tests which are automated by the AI mediated systems (Oracle Team, 2022). The questionnaire on these tests is pre-approved by HR team and candidates are ranked on scores. These online tests help organize and evaluate the suitability of the applicants (D'Silva, 2020). It is so popular that 99 percent of the fortune 500 companies use ATS software (Henderson, 2022; Oracle Team, 2022). Recent trends are towards AI-assisted assessment to help narrow the volume of potential candidates (Hunkenschroer & Luetge, 2022). AI can assess parameters such as hard and soft skills, as well as applicant expectations with regards to role like salary etc. (Laurim et al., 2021). Traits can also be measured via AI-enabled technology through candidate assessment tests. Numerous AI systems facilitate this process, such as skill tests with a gamified approach and AI interviewers (Chen, 2022). Gamified tests contribute to assessing an applicant's character, risk attitude, abilities, motivations, and skills. Furthermore, ML algorithms possess the capability to extract valuable insights from the data of an organization's top-performing individuals, aiding in the identification of specific applicant characteristics linked to enhanced job performance (Hunkenschroer & Luetge, 2022).

Pymetrics is a company that empowers organizations to gauge applicants' soft skills through gamified behavioral AI assessments (Pymetrics Team, 2022b). It offers the capability to evaluate numerical and logical decision-making and analyze digital interviews. Renowned companies like Tesla, LinkedIn, and Unilever, have leveraged Pymetrics to assess candidates. Pymetrics uses algorithm-based online assessment tests, comprising a total of 12 games, each taking 7 to 10 minutes to complete. Typically, assessment consists of 4 games, totaling 25 minutes, chosen based on the specific requirements of the vacant role (Pymetrics Team, 2022a). In the case of Unilever, Pymetrics was utilized, and candidates' results were compared to job success criteria for available positions (Black & van Esch, 2020). If applicants match with the expected requirement of the company, they may proceed to the interview stage.

Interviews whether conducted by human recruiters or AI tools, can be recorded and subsequently analyzed by AI. AI-enabled interviews represent a specific form of assessment where the software evaluates interactions between either human recruiters and candidates or ML and candidates. This entails the AI software analyzing recorded videos of candidates and generating personality profiles based on various factors such as movements, tone, facial expressions, speech, and choice of words (Köchling et al., 2021; van Esch et al., 2019) . The outcome of this analysis, in the candidate personality profile, are compared to the competencies required for the advertised job (Laurim et al., 2021, p. 5497). Scores can also be measured by comparing the "score" of past successful employees. The traits that lead to successful hires can be measured by the AI tool (Black & van

Esch, 2020). There are third-party companies that can be hired to provide AI-based interviews. HirVue is a recruiting-technology firm that has a system that uses “AI-driven assessment” and generates an “employability” score of the applicants based on cameras used to analyze candidates' facial expressions, word choice, and speaking voice (Harwell, 2019). This video-interview software has been used for 12 million interviews worldwide in over 700 different companies (Vertigo, 2020). It measures the candidate's communication skills, empathy, ability to work in a team, and impulsiveness (Vertigo, 2020). It ranks candidates by using NLP to mimic human raters and evaluate interviews (Top Talent Solutions Team, 2022). The AI system asks the candidates various interview questions, and candidates are given 30 seconds to prepare an answer and 3 minutes to respond (HireVueTeam, 2014). HireVue’s system evaluates “hard” and “soft” skills; communication skills, problem solving, initiative, team-oriented etc. (HireVue Team, n.d.). These AI enabled interviews help to narrow the pool of candidates who are later selected for the role. Unilever used HireVue ‘s AI assisted video interviews and found that it decreased time-to-hire by 90%, increased diversity by 16% and allowed them to save over $ 1M (Gee Kee, n.d.).

2.4.8 Selection

The preceding stages are employed to construct a profile of the candidate, aiding in determining their suitability for the role. Recruiters continue to oversee the selection stage, utilizing AI-enabled tools from earlier stages. Presently, human recruiters still make the final hiring decisions, but there is potential for AI involvement at the selection stage. This could represent the next significant advancement in AI participation. While most interviewed recruiters and applicants acknowledge the benefits of AI, they also emphasize the necessity of human intervention (Lisa et al; Horodyski). Research suggests that, at present, AI is not deemed suitable to entirely replace hiring professionals and is viewed as a supporting partner (Levy & Bwomono, 2022).

Currently, the AI tool employed during the selection stage is primarily focused on communication. AI-assistants interact with the candidates and are utilized to inform applicants of their selection status and can be integrated throughout the entire recruitment process to address applicant questions (Chen, 2022; Hunkenschroer & Luetge, 2022; Nawaz & Gomes, 2020; van Esch et al., 2019). Chatbots enable real-time communication while using natural human language, whether through email, personal messaging, or dialogue boxes, with the objective of enhancing the candidate experience while gaining insights into candidate qualities (Upadhyay & Khandelwal, 2018; Navaz & Gomez, 2019). Applicants can apply through chatbots, receive updates, can pose questions, and receive real-time feedback on their application (Marinelli, 2019).

Chatbots can take the load of off recruiters by scheduling meetings for them, updating job databases, answer FAQs, and forwarding emails (Nawaz & Gomes, 2020). Chatbots can efficiently communicate with multiple individuals simultaneously, particularly when issuing multiple rejections, a task that would be time consuming for human recruiters. Applicants can seek explanations from chatbots about their rejection and receive feedback (Johansson et al., 2019; Lisa et al., 2021), allowing chatbots to discern information about the candidate’s emotions (Marinelli, 2021). This information, along with other data collected by the chatbot, can be sent as feedback to the recruiters, optimizing the entire process (Upadhyay & Khandelwal, 2018). Chatbots prove beneficial to both recruiters and applicants, offering the ability to provide prompt and impartial responses compared to human recruiters (Black and van Esch, 2020; Navaz & Gomez, 2019). The listed advantages suggest that chabots have the potential to improve applicant experience. Consequently, even if an applicant is not selected for a particular role, the positive interactions with chat bots may prevent them from being discouraged and could encourage them to apply again to the same company in the future (Nawaz & Gomes, 2020).

2.5 Benefits of e-recruitment with AI implementation

The integration of AI into e-recruitment provides numerous advantages, compelling organizations to shift from traditional to automated approaches (Chapman & Gödöllei, 2017; Handlogten, 2009; Kapse et al., 2012; Omolawal, 2015; Sills, 2014). The key motivations for this shift include:

- Saving time with speed and efficiency of administrative tasks management.
- Achieving better employee matching.
- Reducing in cost.
- Extending reach to a broader range of candidates.
- Accessing all job seekers, including passive candidates.
- Improving corporate image.
- Providing a user-friendly experience for applicants.
- Providing innovative methods for hiring to keep ahead of competitors.
- Decreasing or eliminating human bias.

According to Gartner's 2019 Artificial Intelligence study, recruiters utilizing AI within recruitment found it particularly useful in candidate sourcing (58%), screening (56%), and nurturing (55%). (Lisowski, 2021).

2.5.1 Timeframe (Speed and Efficiency)

One of the most significant benefits of e-recruitment is that it reduces the time and cost to recruit new employees. The average time to hire an employee from when they apply to when they accept a job offer is 40 days. However, this duration is dependent on the type of industry, as it could be longer or shorter for certain industries (Bika, 2021). Additionally, a report from the SHRM states that the average employer spends over $4,700 USD to hire a new employee. This value does not always include advertisements, background checks, and other external factors (Forbes, 2022). Traditional recruitment has “long hiring cycle time, high cost per hire, low geographical coverage, and ineffective candidate relationship management” (I. Lee, 2005, p. 58). In contrast, e-recruitment decreases the time it takes to recruit due to the speed at which the information shared among hiring managers and applicants is sent. E-recruitment processes the incoming applications are received and sorted in an automated form. Since the applications are processed via automated e-recruitment systems, the applicants are immediately informed when their applications are received, processed, and rejected (Mohammed, 2019). The paper trail in terms of applicant attraction, sorting and contact is removed with e-recruitment, instead electronic files replace them and thus speeding up the process (Mohammed 2019, p.51). Additionally, applications can be stored in the companies’ database thus saving them from refilling information for a new application (Evalground Team, n.d.).

A modern approach to e-recruitment would be the use of AI which reduces the time and increases efficiency in the recruitment process (Hoffmann, 2019; Ibrahim & Hassan, 2019). CV screening time is faster with the use of AI than traditional processes. This is beneficial since HR recruiters will have more time to allocate to other duties than screening applicants (Forbes, 2022; Mohammed, 2019). This is helpful for companies that are looking for a faster hiring method, they can adjust and filter for best-fit candidates based on recommended settings (Ibrahim & Hassan, 2019). A Study shows (Lisa et al., 2021) that applicants see the benefit that AI can bring for recruiters as it will speed up the recruitment process, increase efficiency thus helping the businesses to grow and develop. Speed is important in recruitment due to its cost-saving properties, thus gaining a competitive advantage (Black & van Esch, 2020).

2.5.2 Cost

Due to its time-saving benefits, implementing AI methods in recruitment not only enhances efficiency but also leads to cost savings in hiring. The cost of adopting AI techniques in recruitment varies based on the specific needs of the investing company. As mentioned, hiring new employees can cost around $4,700 USD, according to Edie Goldberg, founder of the Menlo Park-based talent management and development company E.L. Goldberg & Associates. Employers often estimate the total cost to hire a new employee to be three to four times the position's salary. Various factors, such as the speed of hiring and the quality of new hires, directly influence the cost-per-hire metric. This includes the time hiring managers spend on resume reviews and interviewing.

In response to the challenges of managing a high volume of job applications, businesses may find it necessary to hire additional recruiters. This is particularly true when the current recruiting team struggles to efficiently review and process applications. Moving to the second stage of recruitment, uploading a job vacancy on the corporate site incurs minimal costs. However, the expense of posting advertisements on other platforms, such as social networking sites, may vary. Despite these variations, the overall cost of recruitment, from initiation to completion, is generally lower than before, as e-recruitment typically saves 24-30% of HR time (Galanaki, 2002, p. 244).The cost-effectiveness of electronic job listings becomes evident when compared to traditional methods such as printed media, agencies, and in-person job boards (I. Lee, 2011). Additionally, online job advertisements have a global reach, attracting a larger pool of candidates and facilitating the identification of more qualified individuals compared to traditional printed media (I. Lee, 2011).

2.5.3 Geographical Range

Unlike traditional recruitment, which was restricted to specific geographical areas, individuals from anywhere in the world can now apply for the same position without any geographical constraints (Ibrahim & Hassan, 2019). This has expanded access and opportunities for both employers and applicants in the job market (Omolawal, 2015), accessible at any time of the day, regardless of the applicant's location. In the past, communication primarily relied on phone calls or letters, which later transitioned to emails. However, with the advent of technology, chatbots now enable faster and more efficient communication. These chatbots use natural language processing to understand and respond to incoming messages (Ibrahim & Hassan, 2019). They play a crucial role in various stages of recruitment, from assisting with application processes to conducting interviews, thereby saving time for both applicants and HR teams. With a stable internet connection, candidates can participate in interviews through two-way communication channels like Zoom or Skype, eliminating the need to travel to the interview location (Ibrahim & Hassan, 2019). This approach broadens the pool of potential candidates and increases the chances of acquiring international knowledge and skills (Dhamija, 2012; Holm, 2012). Furthermore, it facilitates more selective hiring by reaching a larger number of candidates, enhancing the probability of finding a better-fit talent (I. Lee, 2011; Mohammed, 2019). In addition, online recruitment methods ensure that candidates possess a minimum level of computer skills, aligning with the technological demands of modern workplaces.

2.5.4 Hiring Passive Job Seekers and QOH.

Online recruitment systems play a crucial role in targeting and engaging passive job seekers—individuals who browse the internet, come across intriguing job opportunities, but are not actively seeking a job change (Dhamija, 2012). Although these individuals are not actively searching for new positions, they may consider switching jobs if presented with a more appealing opportunity (Mohammed, 2019). One effective strategy to tap into this pool is through employee referrals, where existing employees encourage their contacts to apply to the company's job domains, leading potential candidates to the organization's career sites (I. Lee, 2011). The integration of AI further enhances the likelihood of hiring passive candidates by employing persuasion techniques and sending targeted campaigns (Ween, 2020). AI-activated chatbots or virtual assistants play a crucial role in this process, promptly addressing questions from interested candidates. This two-way communication not only keeps passive candidates engaged but also aids in predicting their willingness to consider a job switch (Upadhyay & Khandelwal, 2018). In addition, advertisements play a vital role in attracting more applicants. Placing ads on traditional career sites may not effectively reach the desired candidates. However, strategically placing targeted ads based on user background activity can significantly increase the number of applicants on the site, thereby expanding the pool of potential candidates, including passive job seekers. This targeted approach ensures that recruitment efforts are focused on individuals more likely to be interested in and responsive to the job opportunities presented. Moreover, the integration of predictive analytics into the recruitment process enhances the quality of hire. Predictive analytics uses data mining and machine learning algorithms to discern patterns and forecast outcomes. In the context of recruitment, predictive analytics can identify the best-fit candidates by analyzing their behaviors and performance. Additionally, it can anticipate the probability of a candidate accepting a job offer or quitting the company within a certain timeframe (Mehta et al., 2013).

2.5.5 Brand Image

The integration of AI in recruitment provides organizations with a competitive advantage, particularly in enhancing their corporate image (Baratelli & Colleoni, 2022; Omolawal, 2015). E-recruitment serves as a platform to communicate career roles, organizational pillars, and user-friendly features for applicants to post and update their resumes on the company's website (Omolawal, 2015). Employers strategically use targeted marketing as a recruitment strategy to align the corporate image with the company's overall brand, attracting new talent (Baratelli & Colleoni, 2022). The use of e-recruitment, characterized by ease of use, speed, and 24/7 availability, contributes to enhancing the employer brand. Candidates often find it more comfortable to apply for roles remotely compared to traditional methods (Omolawal, 2015). The incorporation of AI in recruitment further supports and reinforces brand image, portraying the organization as innovative and capable of attracting top-tier candidates (Ween, 2020). Brand image, encompassing advertising and reputation, correlates with high levels of recruitment practices and the attraction of quality applicants (Collins & Han, 2004). While brand image alone may not suffice for a competitive advantage (Ween, 2020, p. 93), a study by Baratelli & Colleoni (2022) involving 302 participants, indicates that AI-enabled tools positively impact employer brand image, thereby enhancing talent attraction. The study identifies five dimensions influencing employer image: interest value, social value, economic value, development value, and cooperation value. AI-enabled recruitment plays a crucial role in three main activities: outreach, screening, and assessment. In outreach, AI can tailor methods to target specific candidates through personalized emails, pop-ups, and other means. The screening stage, accelerated by AI, efficiently sorts through resumes based on predefined criteria, increasing speed by 60% to 90% and efficiency by 25%. The pre-selection stage further narrows the candidate pool, and AI systems are perceived as less biased and more objective (Lisa et al., 2021). The factors of accuracy, velocity, reliability, and unbiasedness significantly impact AI-enabled recruitment, contributing to a positive perception of the role of AI-based technology in recruitment and, consequently, enhancing employer brand image (Baratelli & Colleoni, 2022). AI plays a key role in enhancing employer brand image through positive candidate experiences. Tools like chatbots and virtual assistants provide a user-friendly and personalized journey for candidates. These technologies offer real-time interactions, instant feedback, simplified interview slot booking, and quick automated responses, improving the overall candidate experience. This positive interaction not only strengthens the organization's reputation but also contributes to increased brand loyalty, word-of-mouth recommendations, and a favorable perception among potential future candidates.

2.5.6 Human Biases

AI plays a significant role in mitigating bias, although it faces challenges in interpreting emotions and context (Ween, 2020). Its effectiveness is contingent on the model's construction, with biases potentially stemming from programmers or the data it processes. Bias, involving unfair favoritism or prejudice toward a person, group, or idea, can be consciously or unconsciously ingrained in AI (Ween, 2020). The dataset fed into the algorithm may be skewed, favoring certain skills, and resulting in negative preferences toward specific individuals. Therefore, setting up an appropriate algorithm is crucial for AI to perform accurately (Ween, 2020). Ensuring data reliability is equally important to hire candidates with the right skill set. Although biases are challenging to avoid, appropriately designed AI models can help decrease bias in recruitment.

Prejudicial attitudes in recruitment exist, as demonstrated by Purkiss et al. study in 2006, which revealed a significant interaction between applicants' names and accents, influencing recruiters' assessment of applicant's characteristics. Specifically, those with accents are perceived less favorably by interviewers compared to those without an accent, nicknames likewise those with ethnic names were viewed less favorably than those without ethic names. This has tangible implications for hiring decisions, highlighting the need for a proactive measure to foster unbiased evaluation in the recruitment process (Segrest Purkiss et al., 2006).

Diversity is emphasized for the success of organizations, as diverse teams are known to be more productive, innovative, and engaged (Upadhyay & Khandelwal, 2018, p. 256). Mitigating biases in hiring algorithms can contribute to increased organizational diversity, fostering a better team. AI enables the reduction or elimination of certain biases in the recruitment process (Lisa et al., 2021), aiding in objective decision-making compared to traditional, more subjective methods. Algorithms, with the right safeguards, enable transparency and ability to detect discrimination (Kleinberg et al., 2018). In a qualitative study in Sweden, both recruiters and candidates acknowledged the benefits of AI in decreasing bias and promoting objective decision-making Lisa et al., (2021). While AI proactively fights bias, it is not entirely immune to it (Raub, 2018; Upadhyay & Khandelwal, 2018). Its lack of human necessities, such as rest, makes it advantageous, as human errors due to fatigue are probable. Emotional and personal states of interviewers can lead to irrational decisions, potentially resulting in missing out on hiring the best talent (Bhalgat & Ghahremanzamaneh, 2019). AI, devoid of emotion, excels in making objective decisions and bypasses these issues.

2.6 Drawbacks and Adoption Challenges of AI in E-Recruitment

Implementing AI within the recruitment process comes with potential pitfalls, often stemming from deficiencies in data sets or improper algorithms (Ween, 2020). Ethical concerns and increased expenses can arise from issues such as privacy, data errors, bias, emotional or social intelligence, and status. One of the most recurring concerns among applicants is the lack of transparency in the use of AI-enabled technology in recruitment (Chen, 2022; Lisa et al., 2021; Ween, 2020). Despite these challenges, AI-assisted hiring has experienced a significant surge, accelerating by 270% in just four years (Costello, 2019). Concerns related to e-recruitment vary among employers and job seekers. Singh Hada & Gairola (2015) outlined challenges faced by employers, including high implementation fees, the need to sift through fake candidates' profiles with potential misinformation, and the absence of a personal touch in the online recruitment process. Recruiters may struggle to grasp the personality of candidates in an online setting. Job seekers, on the other hand, face challenges such as impersonal interactions, concerns for privacy, responding to outdated job listings, and the possibility of receiving no response. Figure 2.6 illustrates the list of challenges faced by employers and job seekers, adapted from various sources (Chuks Okolie & Irabor, 2017; Ore & Sposato, 2021; Singh Hada & Gairola, 2015; Ween, 2020).

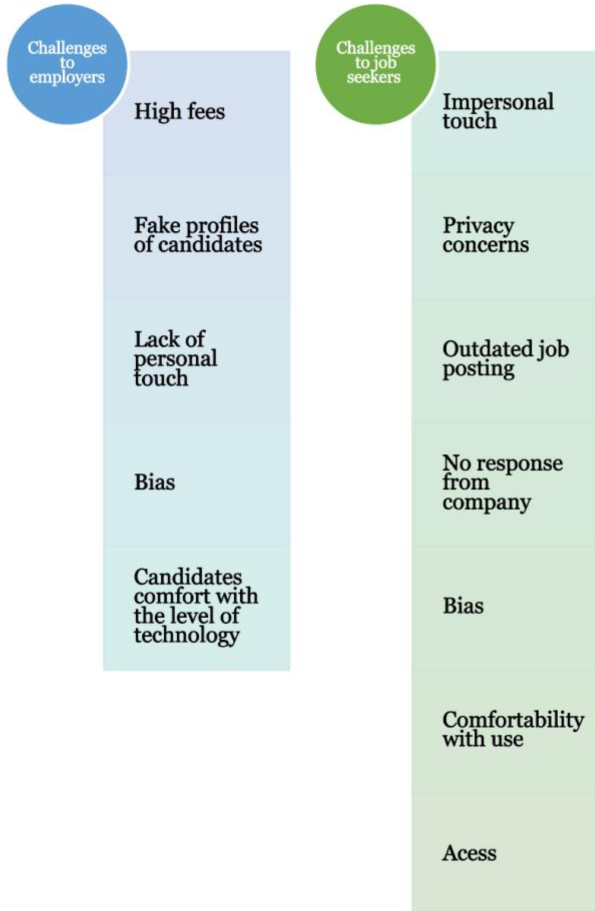

Figure 2.6 Displays the challenges faced among employers and job seekers. adapted from (Chuks Okolie & Irabor, 2017; Ore & Sposato, 2021; Singh Hada & Gairola, 2015; Ween, 2020)

2.6.1 Bias & Discrimination

While there are numerous benefits to implementing AI in recruitment, the potential for misinformation or inadequate scrutiny may amplify biases. AI is designed to help eliminate or reduce bias in hiring, yet it may inadvertently introduce or perpetuate biases. Despite the ideal goal of algorithms aiding human recruiters in avoiding personal prejudices, they may carry risks of intended or unintended biases, sharing the same biases as their programmers. Natalie Cramp, CEO of data science consultancy Profusion, emphasizes that algorithms are subjective views in code, not objective entities (O'Dea, 2022). The training data input into algorithms essentially reflects the biases of those providing it. In the sourcing stage, job boards and algorithmic ads target "relevant" job seekers based on superficial predictions. However, this approach may inadvertently reinforce racial and gender stereotypes (Bogen, 2019). Algorithmic biases can emerge when the model replicates the patterns of human recruiters. For instance, if a recruiter frequently interacts with white males, the algorithm might prioritize candidates with similar characteristics, potentially sidelining others. Resume evaluations are often keyword-based, either input by HR teams or developed with machine learning tools. This approach, while efficient, can perpetuate biases if the keywords are derived from previous successful hires that share commonalities. If the model is trained on biased data, it may unintentionally favor or disfavor certain groups, this is because “algorithms do not question the human decisions underlying a dataset” (Barocas & Raghavan, 2019).

Regulating models is crucial to address biases in AI recruitment. Furthermore, if the training data is “inaccurate, unrepresentative, or biased” the model’s predictions will reflect this (Bogen, 2019). Amazon's 2014 selection tool, for example, faced issues as it exhibited gender bias and favored unqualified candidates. The model, trained on predominantly male-based data, consequently, it discriminated against women candidates (Dastin, 2018; Ween, 2020). Accessibility, inclusivity, and fairness are essential considerations in AI recruitment. There's a concerning trend where recruiters are less likely to hire individuals disclosing disabilities on their applications, and disabled individuals are often paid less than their abled counterparts (Ameri et al., 2018). Ableist bias is particularly significant in emotional recognition models that may misinterpret facial expressions of individuals with certain conditions if not adequately represented in training datasets (Guo et al., 2019). Speech systems in AI, which recognize speech patterns and attributes, may disadvantage candidates with speech impairments (Fok et al., 2018; Tilmes, 2022). Likewise, colloquial language and spelling errors can jeopardize how chatbots understand and respond to questions (Marinelli, 2021). Candidates may harbor anxieties about AI's potential for bias and discrimination in recruitment, raising concerns about trustworthiness, accuracy, and reliability (Ore & Sposato, 2021).

2.6.2 Dehumanization

The implementation of e-recruitment, particularly in online interview processes, may have implications for the quality of the applicant's user experience. There are concerns about user-friendliness, especially for individuals who may not be tech-savvy (Handlogten, 2009). Despite this, e-recruitment is deemed more user-friendly as applicants can access portals 24/7 from any location, reducing reliance on paper applications (Chuks Okolie & Irabor, 2017). Dr. Samuel Omolawal found a potential drawback in e-recruitment, highlighting a lack of personal interactions and hindered communication flow, leading to frustration among applicants (Omolawal, 2015). AI-based interviews may contribute to this impersonal feeling, focusing on specific questions without providing ample opportunity for applicants to share their stories (Chuks Okolie & Irabor, 2017). Emotional intelligence is a key aspect lacking in AI-powered technology, as algorithms may struggle to recognize context, potentially disadvantaging candidates (Ween, 2020). Relying solely on AI, especially chatbots, for candidate interactions could pose a challenge. Candidates require opportunities to assess the company culture and the individuals they'll be working with. Evaluating the vibe and environment of the workplace is crucial for a candidate to determine if they align with the company's values. While deciding if they enjoy interacting with a chatbot is not as vital, as the real interactions will be with human colleagues once they secure the role (Black & van Esch, 2020). Privacy and data security are additional challenges in e-recruitment, with organizations providing privacy statements to address concerns (Omolawal, 2015). AI-enabled systems may have the ability to collect personal data, even networking sites like LinkedIn and Indeed store data from online assessment tests, raising potential privacy issues. Another challenge is internet access, as individuals without continuous access may be disadvantaged. Lack of internet connectivity can hinder applicants from checking the status of their applications (Singh Hada & Gairola, 2015). Additionally, in AI-based video or audio recruitment, candidates need access to a camera or microphone. The quality of technology used during online interviews can impact the candidate's performance, potentially creating disparities based on the equipment's quality (Dhamija, 2012).

2.6.3 Fear of AI

Recruiters and companies benefit from e-recruitment due to its easy access and ability to handle a high volume of resumes. However, this efficiency can lead to many resumes, impacting response times and causing candidates to lose interest (Ween, 2020). Speed is considered an advantage in recruitment, but a poor algorithm may accept applicants who don't meet criteria, requiring adjustments and proving time-consuming and costly (Ween, 2020). The introduction of AI for candidate interviews and other uses raises concerns among recruiting staff about potential job automation (Lisa et al., 2021; Ween, 2020; Marinelli, 2021). On the contrary, it is also believed that automation could open new job positions (Ween, 2020). Likewise, legal concerns arise in the final selection of applicants and hiring decisions, particularly in jurisdictions where such decisions require a human like the General Data Protection Regulation in the EU (Laurim et al., 2021). Surveys indicate a growing acceptance of digital tools in recruitment, with a high percentage of consumers preferring chatbots over human interaction (Bajor, 2022). However, adopting automation in recruitment processes, including candidate sourcing and screening, may be hindered by budget constraints, with 68% of recruiters citing cost as a barrier (Dolores & Morales, 2020). Despite potential benefits, applicants may struggle to trust AI-enabled tools, as digital interviews are perceived as less personal and somewhat "creepy" compared to human-led interviews (Langer et al., 2017).

Chapter 3: Methodology

3.1 Assumption of Research Philosophies

Research philosophy encompasses the beliefs and assumptions guiding knowledge development (Saunders et al., 2009, p.130; Zukauskas, 2018). These assumptions fall into three key dimensions: ontological, epistemological, and axiological. Ontological assumptions pertain to the realities encountered in research, addressing the fundamental nature of reality (Saunders et al., 2009; Žukauskas et al., 2018). Epistemological assumptions concern human knowledge, exploring what can be known and how it is known (Ahmed, 2008). Axiological assumptions revolve around the researcher's worldview and the influence of personal values on the research process, essentially the role of ethics (Saunders et al., 2019). The summary of the methodology used in this thesis can be found in Table 3.1.

3.2 Research Paradigms

Žukauskas et al., (2018), and Saunders et al., (2019) describe various research paradigms, whose importance varies depending on the field of study. They describe positivism, post-positivism, interpretivism/constructivism, transformative, and pragmatism. Positivism relies on testable theory and is confined to observable and measurable phenomena. Positivists maintain neutrality and detachment from research findings to avoid any influence, dissociating themselves from personal values (Žukauskas et al., 2018). Post-positivism combines empirical observations and logical reasoning to infer conclusions from data. In contrast, interpretivism, as a social method, aims to generate meaning. Background information, such as ethnicity, culture, and other social science factors, needs consideration as they can influence meaning under different circumstances. This approach involves examining the perspectives of different groups since each may experience a different reality based on their beliefs or culture (Saunders, 2009). Realism incorporates principles from both positivist and interpretivist research philosophies. A realistic research philosophy is grounded in assumptions necessary for perceiving the subjective nature of human experience, focusing on understanding the cause of what is seen and experienced. Postmodernism assigns multiple meanings to experiences and values the diverse opinions of individuals over predetermined views. Pragmatism employs the most useful method(s) for a specific investigation, considering practicality, context, and the research question. The choice of research philosophy is determined by the research problem (Žukauskas et al., 2018).

Considering our research problem which aims to gain insight on the perspectives of AI experts, recruiters, and applicants regarding AI at various stages of the recruitment process, the pragmatism standpoint aligns well with our objectives. It emphasizes practical outcomes and uses the methods and theories that work best for achieving the goals (Saunders et al., 2019). This research adopts a problem-centric focus, where pragmatism emphasizes solving real-world problems and achieving practical outcomes. We are addressing practical issues related to AI in recruitment by seeking to understand measurable perceptions and potential differences among AI experts, applicants, and recruiters. We also focus on how AI is being used in the recruitment process and explore its potential applications. Our approach is mainly quantitative through a survey questionnaire.

However, we do have a qualitative open-ended question for additional details which reflects a pragmatic approach. This method allows us to gather both numerical evidence and subjective insights, enhancing the comprehensiveness of the findings.

3.3 Inductive, Deductive, and Abductive Research

Generally, there are three fundamental approaches to scientific inquiry: inductive, deductive, and abductive research. Deduction involves the development and validation of a theory through empirical observations or experiments. It begins with assumptions derived from existing theory and tests whether this theory holds true in specific cases. Deductive research is characterized by the search to determine and explain the "relationship between concepts and variables" (Saunders et al., 2019, p. 154). It should be used so that facts can be quantitatively measurable. The inductive approach is open and exploratory, involving the development of theories from observations and data. It searches for patterns to determine a generalized conclusion and is commonly used in emerging fields and new research areas. While inductive research typically leverages qualitative methods, it is not limited to them. The abductive research approach combines both inductive and deductive reasoning. It is utilized to explore phenomena, identify themes, and explain patterns.

As discussed in Chapter 2, perceptions of AI in recruitment have been measured for applicants and recruiters, but research on this topic is still in its infancy (Boyd, 2022; Lisa et al., 2021; Robinson, 2018). The measures used in this thesis were developed by other researchers, and Section 3.11 outlines the purpose of these measures (refer to Appendix A for items). Our goal is to use these measures to quantitatively understand the perceptions of applicants, AI experts, and recruiters, and to determine if there are significant differences between these groups. Additionally, we aim to explore if these perceptions differ across various stages of the recruitment process. Therefore, we have selected the inductive approach to address our research questions, utilizing a quantitative survey to collect relevant data from all three participant groups based on their roles: applicants, AI experts, and recruiters.

3.4 Methodological Choice

Several research design options exist, including explanatory, exploratory, descriptive, and predictive approaches. Predictive theory involves a set of theoretical statements that generate predictions, while descriptive theory focuses on careful observation and detailed documentation to characterize a population, situation, or phenomenon. It adheres to scientific methods and emphasizes replicability. Explanatory theory provides explanations through a set of theoretical statements.

Exploratory theory, often employed in relatively new topics, is flexible and can be either qualitative or quantitative. It is particularly useful when researchers have limited awareness of the research issue (Saunders et al., 2019). In this thesis, our objective is to comprehend the measurable perceptions of AI experts, applicants, and recruiters, investigating potentially significant differences between them (RQ2 and RQ3). Our chosen research design is exploratory as we aim to delve into how AI is utilized at various stages of the recruitment process and explore potential applications (RQ1). This involves uncovering and understanding the current landscape, identifying diverse uses, and exploring potential applications in the realm of AI and recruitment. Likewise, pragmatism embraces exploratory research approaches.

3.5 Research strategy

The research methodology employed in this study follows a quantitative approach, aligned with positivism, which involves the systematic collection and statistical analysis of numerical data. Using a survey questionnaire method, data was gathered to uncover user perspectives and supply numerical evidence to address the research questions outlined in Chapter 1. Employing statistical techniques, the analysis sought to identify patterns, relationships, and associations within the data. Our research strategy places a strong emphasis on measurable outcomes, recognizing the valuable insights that quantitative research approaches can provide. However, it acknowledges the inherent limitations of quantitative methods and thus incorporates qualitative research approaches to delve into the subjective meanings of the data. To facilitate this exploration, an open-ended question was included in the survey, allowing participants to optionally provide additional details and express any nuanced aspects not captured by the quantitative responses. This combination of quantitative and qualitative approaches aims to offer a comprehensive understanding of the research subject.

3.6 Method

This study employed a cross-sectional survey design to gather data on the perceptions and attitudes of participants regarding the use of AI in different stages of the recruitment process. The survey was structured to address the research goals and objectives of the study, which aimed to understand how AI is perceived in various recruitment stages, explore the influence of AI knowledge on perceptions, and assess differences in viewpoints among different user groups. Surveys are particularly suited for collecting data from a large and diverse sample of participants quickly and cost-effectively (Anderson, 2021). The data was collected at a single point in time, there was no follow-up or longitudinal data collection. The questionnaire was structured with multiple closed questions with fixed options to choose from in multiple-choice ordinal fashion. We also had one open-ended question at the end. Closed questions helped the researchers as they elicit one solid response, which makes the easy to comprehend and interpret (Bell et al., 2019). A questionnaire can help collect multiple types of data (Matthews & Ross, 2014). In this research, data was collected on multiple variables related to participants' perceptions and attitudes regarding AI in recruitment. Cross-sectional studies often involve the measurement of multiple variables or constructs in a single data collection phase. Cross-sectional studies aim to capture a snapshot of a population at a given point in time (Bell et al., 2019). In this case, we sought to understand the current perceptions of participants regarding AI in recruitment. The questionnaire consisted of eight distinct scenarios, each representing a different recruitment stage where AI could potentially be employed. These scenarios aimed to provide participants with a clear understanding of how AI could be used and allowed them to evaluate its utility and fairness at each stage. Participants were asked to rate their perceptions and attitudes using a standardized Likert scale, where higher scores indicated more positive attitudes and perceptions.

Table 3.1 Summary of Methodology and Approach

Methodological assumption	*Selected approach*
Research paradigm	Pragmatism
Research approach	Inductive
Research design	Exploratory
Methodological choice	Quantitative and one open-ended question
Method	Survey questionnaire
Time horizon	Cross-sectional
Technique and Procedure	Goggle Forms, Prolific platform, IBM SPSS, Excel datasheet

3.7 Sampling

There are two primary sampling methods: probability and non-probability sampling (Saunders, 2009). Probability sampling, also known as "random sampling," ensures that every member of the population has an equal chance of being selected. In contrast, non-probability sampling involves a subjective selection process, making the sample non-random (Bell et al., 2019). These methods also differ in sample sizes, with qualitative studies typically employing smaller sample sizes due to the time-intensive nature of data gathering and analysis, while quantitative studies involve larger sample sizes (Saunders et al., 2019). In exploratory research, purposive sampling is commonly used to gather the maximum amount of information by intentionally selecting participants based on specific characteristics. Purposive sampling is contrasted with convenience sampling, where participants are recruited based on availability and practicality (Bell et al., 2019). Snowball sampling, a form of non-probability sampling, falls under the umbrella of convenience sampling. In snowball sampling, the researcher initiates contact with relevant participants, expanding the participant pool through referrals from initial contacts (Bell et al., 2019).

This thesis employs a quantitative research method and adopts a hybrid approach by combining purposive sampling with networking or snowball sampling based on available contacts. This hybrid method aims to achieve a more diverse sample representation within the population, identifying varied perspectives within similar roles. The goal is to explore user perspectives on AI in the recruitment process, targeting individuals with knowledge of AI (AI experts) and those affected by its implementation (applicants and recruiters). We have selected our user group to have basic knowledge of AI. Additionally, we used the platform *Prolific* to increase our sample size, particularly among recruiters with experience in the recruitment process.

3.8 Demographics overview

The survey was remotely distributed to 127 individuals. After applying an attention check question to ensure the quality of responses, 123 valid responses remained. The survey participants were categorized into three distinct user groups: 19 respondents identified as AI experts, representing 15% of the sample; 34 individuals identified themselves as recruiters, comprising 28% of the participants, while the majority, with 70 responses, identified as applicants, accounting for 57% of the sample. Among the 123 survey respondents, 44% were female, 52% were male, and 4% chose not to provide gender-related information, see Figures 3.1 to 3.4 for demographic overview.

To qualify as an applicant, individuals were required to have applied to and participated in the recruitment process for at least five different roles in the last five years. This criterion aimed to ensure that participants had recent and relevant experience as candidates in the recruitment process. Recruiters were included if they had previously worked or were currently working in recruitment. For individuals to be categorized as AI experts, they need at least three years of professional experience in the AI industry. These criteria were employed to assemble a diverse group of participants who could provide valuable insights based on their respective experiences and expertise in recruitment and AI.

All participants were asked to answer several questions prior to the survey to gain a comprehensive understanding of participants' attitudes toward AI (see Appendix A). The questions were designed to explore participants':

- Experimentation Propensity (D1), measuring their openness to experimenting with new information technologies.
- Early Adoption Tendency (D2) to see if the participants in our study are eager to try out new technologies.
- Understanding Hesitancy towards New Technologies (D3) provided context for overall comfort levels and potential concerns related to AI.
- Confidence in AI Decision-Making (D4).
- AI Confidence in Data Analysis (D5) was assessed to gauge their trust in AI capabilities.
- Confidence in AI for Personalized Decisions (D6) examined their trust in AI for personalized simple tasks like creating recipes for cooking.
- Preference for AI in Routine Transactions (D7) indicated experience with AI for simple activities, or chatbot style conversations.
- Familiarity (D8) with the Term "Artificial Intelligence".
- Knowledge of AI Applications (D9) to understand their awareness, influencing subsequent perceptions and expectations regarding AI, particularly in recruitment scenarios.

The demographic responses were recorded using a 5-point Likert scale, ranging from strongly disagree to strongly agree. Respondents indicated their level of agreement with the demographic questions. Individual responses, means based on role, and ANOVA testing were employed to analyze the data. The survey revealed consistently high or positive scores, with participants scoring between 4 and 5 across D1, D2, D5, D6, D7, and D8, regardless of their roles. Notably, participants showed low scores (1 for strongly disagree to 2 for disagree) on D3, suggesting that they are not hesitant to adopt new technologies. This indicates their openness to experimentation and willingness to explore novel concepts. Furthermore, participants expressed a range of sentiments, spanning from neutral to agreement, regarding their confidence in AI decision-making processes and outcomes (D4). A noteworthy observation emerged when conducting ANOVA testing on D4, revealing a significant difference among participants with a p-value of 0.0368. AI experts demonstrated a mean confidence score of 3.79, whereas applicants and recruiters scored 3.17 and 3.44, respectively. These findings suggest that AI experts express a higher level of confidence in the decision-making processes of AI compared to applicants and recruiters. Overall, the data indicates a prevalent perception that AI outputs are considered accurate or acceptable, emphasizing a noteworthy level of trust in the capabilities of artificial intelligence within the surveyed cohort. For a detailed breakdown of the codes and demographic questions, please refer to Table 7.3 in Appendix A. Table 7.3 provides information on the coding structure and demographic inquiries. Additionally, for a thorough understanding of the mean scores and their variability, consult Figure 7.4 in Appendix A. For a view on trend of response for demographic questions see Figure 7.1 in Appendix A.

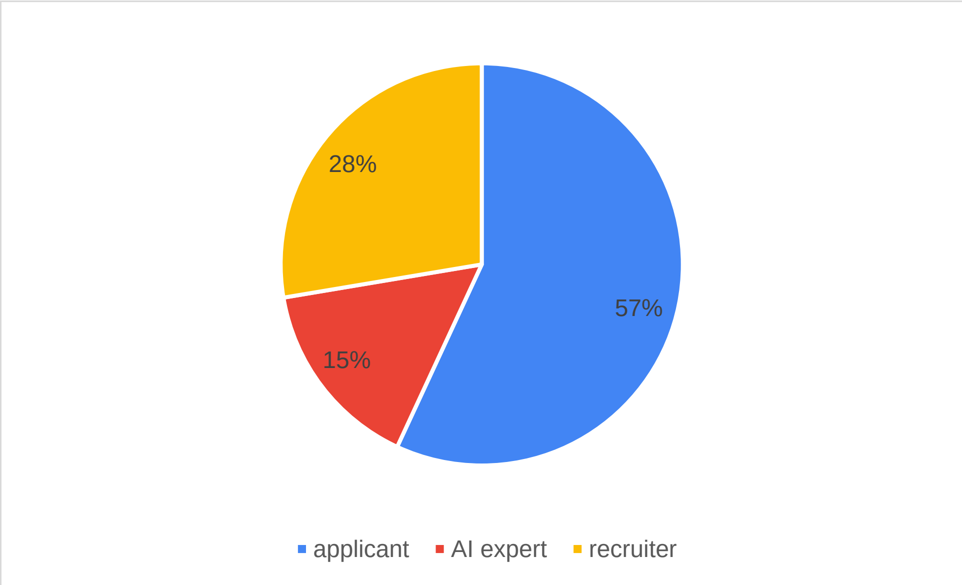

Figure 3.1: Charting Participant Role Distribution

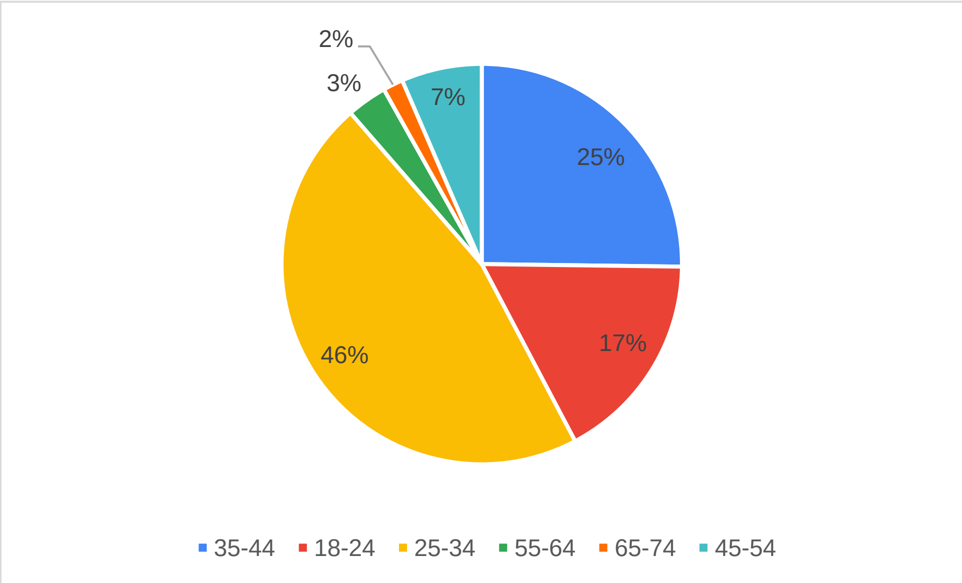

Figure 3.2: Charting Age Distribution Among Participants

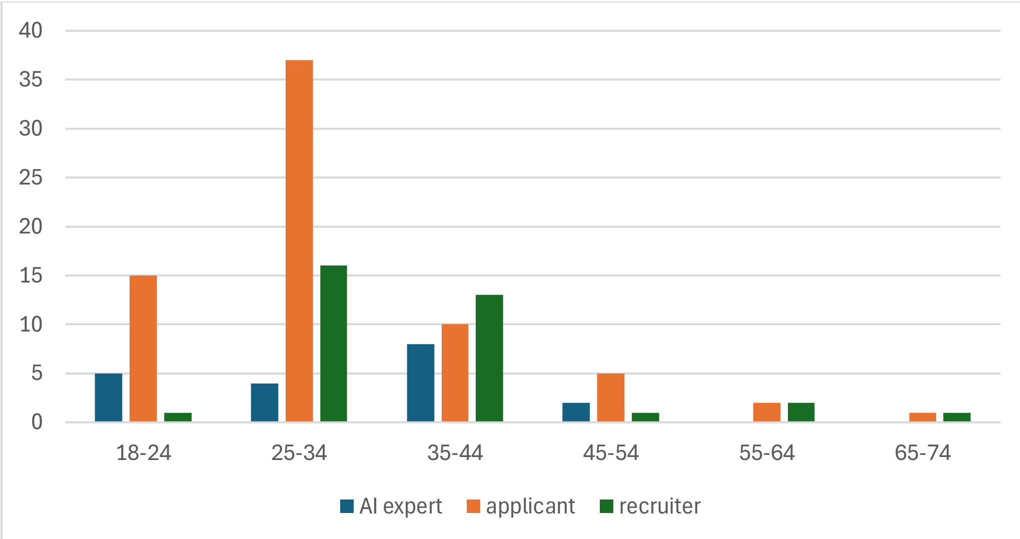

Figure 3.3: Visualizing the Demographic Roles of Each Age Group of Participants

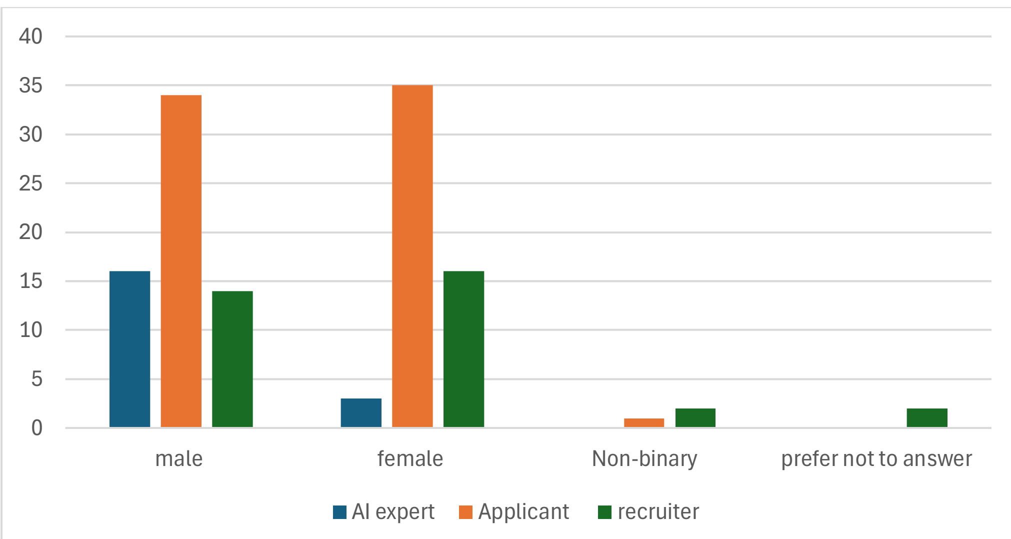

Figure 3.4: Gender Distribution Analysis by Participant Role

3.9 Survey Questionnaire

The survey was distributed through LinkedIn on various survey and research pages. Additionally, professors that perform research in AI were requested to share the participation poster with their contacts who are AI experts. This approach aimed to ensure that genuine AI experts were included in the study participant pool. Data collection took place throughout May and June 2023, and the survey was made available on the Prolific platform through Google Forms. The survey comprised eight scenario descriptions and utilized closed-ended multiple-choice questions with an ordinal scale ranging from 1 to 5. All questions, except the final open-ended one, were mandatory. The last question encouraged participants to express their views on AI in the recruitment process based on the presented scenarios. Demographical questions helped establish a general understanding of the survey participants to provide insight on their experiment propensity, early adoption tendencies, hesitancy towards new technologies, and overall confidence in AI across various applications. The scenarios covered various aspects, including:

S1. AI assistance in crafting job roles and descriptions by optimizing language to attract diverse and qualified candidates.
S2. Leveraging ATS to streamline the application process and manage applicant data.
S3. Employing AI for resume screening and sorting, enabling quick identification of relevant skills and qualifications.
S4. Facilitating gamified assessments to assess candidates' skills and competencies.
S5. Conducting digital interviews with avatar interviewers.
S6. Utilizing AI in candidate selection processes.
S7. Communicating selection outcomes through interactive and personalized chatbots.
S8. Supporting ongoing communication between candidates and potential employers through chatbots addressing queries.

Additional details can be found in Table 7.1 in Appendix A.

3.10 Measures

Research has demonstrated the significance of transparency when incorporating AI into the recruitment process, as observed by (van Esch et al., 2019). Applicants often express the desire to be informed when AI technologies are utilized in recruitment, as a lack of transparency can create feelings of suspicion and unease (Langer et al., 2021). Moreover, studies have indicated that candidates' attitudes toward AI play a substantial role in determining whether they will complete the application process (van Esch et al., 2019). This underscores the reason and importance of clearly specifying how and where AI is employed in each of the eight scenarios that represent various stages of the recruitment process.

In each of the eight scenarios, we assessed nine distinct scales, each comprising multiple items. These nine scales encompass a comprehensive evaluation of various aspects relevant to our study. The scales include:

- Organizational Attractiveness
- Creepiness
- Perceived Validity, Accuracy, & Trust
- Privacy Concern
- Fairness
- Opportunity to Perform
- Two-way Communication
- Usefulness
- Satisfaction

The scales used in this study were derived from various organizational justice theories, as well as Job Pursuit Intention, Technology Acceptance Model (TAM), and the Creepiness of Situation Scale (CRoSS) (Colquitt, 2001; Langer & König, 2018; Natasia et al., 2022; Figueroa-Armijos et al., 2023).

Organizational justice theories suggest that applicants hold pre-existing fairness criteria (Gilliand, 1993). Procedural justice, encompassing fairness measures, serves as a heuristic for applicants to assess the fairness of selection outcomes (Nikolau & Georgiou, 2018). Applicants are influenced by the outcomes of the selection process, such as hiring or rejection (Colquitt, 2001; Gilliand, 1993; Nikolau & Georgiou, 2018). Since this thesis focuses solely on gathering information about the procedure and use of AI at a specific step, without explicitly addressing perceived outcomes, measuring the favorability of selection outcomes was deemed unnecessary.

There are four dimensions of justice rules: interpersonal, procedural, distributive, and informational justice (Colquitt, 2001). Informational justice involves providing honest explanations for decision outcomes (Colquitt, 2001; Schlicker et al., 2021). Given the study's objective of assessing perceptions of the procedure rather than views on outcomes, informational justice was excluded. Similarly, since the scenarios presented in this thesis were hypothetical and not based on real interactions between recruiters and applicants, only the measure of two-way communication was collected for interpersonal justice. Interpersonal justice pertains to the quality of treatment and respect received by the applicant.

Based on the research questions and scenario descriptions, procedural and interpersonal justice were prioritized. The selection of measures was guided by their relevance to the research questions. Measures of fairness, accuracy, and opportunity to perform were collected from the procedural justice rules. Job pursuit intentions aided in assessing organizational attractiveness, while the Creepiness of Situation Scale (CRoSS) gauged discomfort related to novel technologies. Two measures were drawn from the Technology Acceptance Model (TAM) — usefulness and satisfaction. Finally, privacy concerns were addressed as an ethical consideration.

Refer to Figure 3.5 to visualize the individual scales. Measures, items range from 1 (strongly disagree) to 5 (strongly agree). The control variables will be measurements of age, gender, technological affinity, and knowledge of AI. Technological affinity and knowledge of AI was used to determine the consensus of AI use or familiarity. Technological affinity will be measured with three items from (Agarwal & Prasad, 1998), e.g., “If I heard about a new information technology, I would look for ways to experiment with it”.

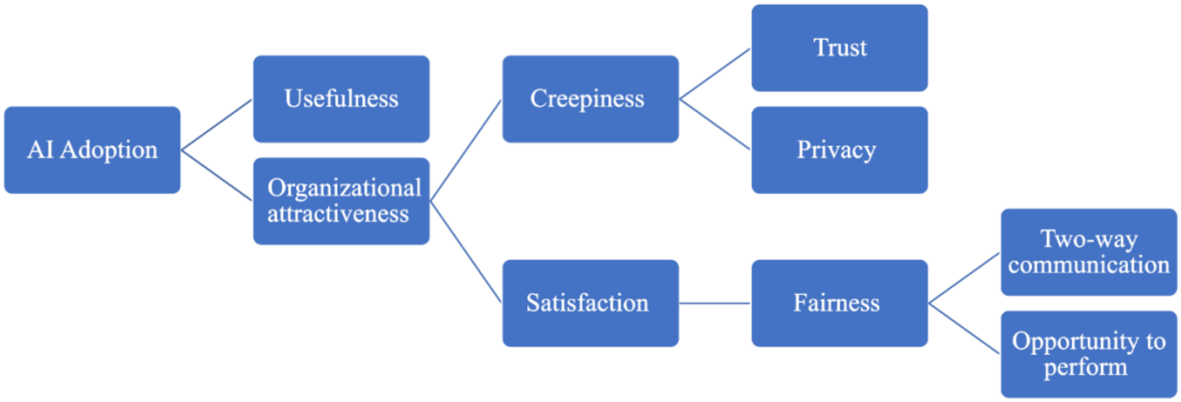

Figure 3.5 Measures in AI Adoption Assessment.

3.10.1 Organizational Attractiveness

Organizational attractiveness is the degree of perceived attitudes towards organizations (Highhouse et al., 2016). It plays a significant role in shaping perceptions of an organization, with attracting top talent emerging as a primary concern for organizations. Employer branding is recognized as a strategic approach to gaining a competitive advantage in the war for talent (Baratelli & Colleoni, 2022). Organizational attractiveness is a predictor of job pursuit intentions (Chapman et al., 2005). Job pursuit intentions are an indication of how much an applicant wants to continue to engage with the recruitment process, including submitting applications, attending interviews and assessments, and potentially accepting a job offer if one is extended (Smither et al., 1996; Warrenbrand, 2021). In contrast, if the applicant has negative views on the organization they could withdraw from the candidate pool, speak ill of the company, and may not pursue a career at the company (Smither et al., 1996; Warrenbrand, 2021). Therefore, it is important for a candidate to have positive organizational perceptions because the success of the company's selection process is reliant on it.

AI, acknowledged as a key driver for innovation, is crucial for obtaining a competitive edge (Weinert et al., 2020). The perceived organizational innovation becomes a critical criterion for selecting potential employment (Sivertzen et al., 2013). Weinert et al., (2020) findings suggest that the use of advanced AI-based recruitment methods positively impacts perceived employer attractiveness. Conversely, earlier research, including studies by Acikgoz et al. (2020) and Kaibel et al. (2019), has delved into organizational attractiveness by comparing organizations using AI in their hiring processes with those that do not. Their findings often indicate that users tend to perceive organizations employing AI hiring methods as less attractive. Additionally, studies have established a link between organizational attractiveness and the likelihood of recommending a company to others. Perceived ease of use, particularly in terms of usability and timesaving (Sylva & Mol, 2009), is a key factor influencing this perception. Research results on organizational attractiveness with AI implementation have been mixed. According to Kochling et al.'s (2022) findings, AI support in later recruitment stages, such as video interviews, leads to a decrease in the Opportunity to perform and an increase in emotional creepiness, ultimately diminishing organizational attractiveness.

This study aims to assess whether candidates would still apply for a role and find an organization attractive when AI tools are integrated into their recruitment process. Specifically, we investigate which stage of the recruitment process with AI implementation, if any, users find organizations attractive or not. We adopt a fully transparent model, ensuring that survey respondents are informed about when and how AI is used at each step of the recruitment process. This level of transparency, as emphasized by Langer and König (2018), can significantly influence how attractive an organization is perceived. Measures for organizational attractiveness are derived from Langer et al. (2021). Organizational attractiveness will be assessed and measured using the General Attractiveness Scale developed by Highhouse et al., (2003) taken from (Langer et al., 2021), consisting of 5 items, e.g., "For me, this company would be a good place to work," on a 1–5 Likert scale.

3.10.2 Creepiness

Consideration of emotions is crucial in understanding user acceptance of recruitment methods. Unfavorable emotional reactions from applicants can often be attributed to a sense of creepiness (Hiemstra et al., 2019). Creepiness, as a complex emotional response, is characterized by a feeling of discomfort and uncertainty, typically triggered by unfamiliar situations or interactions with new technologies (Langer & König, 2018). In the context of AI in recruitment, individuals might experience creepiness when encountering unfamiliar technological interactions, especially when they cannot predict how the technology behaves or its intentions (Polonetsky & Tene, 2015). Ambiguity in the technology's role, decision-making processes, or its handling of personal information and privacy can exacerbate feelings of discomfort. This understanding of creepiness is valuable for designing technologies and interactions that minimize negative emotional responses and reduce perceptions of creepiness.

Two key measures are employed to dissect the elements contributing to creepiness in scenarios: emotional creepiness and creepiness ambiguity. Emotional creepiness relates to the discomfort and unease individuals feel when faced with unpredictable or unpleasant situations, including interactions with technology. On the other hand, creepiness ambiguity refers to the uncertainty and discomfort arising from a lack of clarity on navigating or judging specific situations. Identifying the aspects in the scenarios that trigger these feelings helps developers mitigate and reduce unsettling experiences—a crucial consideration for recruitment companies and experts looking to enhance AI tool acceptance in the recruitment process.

Perceived creepiness and ambiguity in technology often stem from unpredictability. For instance, a study by Langer et al. (2017) found that applicants perceived digital interviews as "creepier" than videoconference interviews due to their unfamiliarity and lack of real-time interaction with human interviewers. Digital interviews, in which applicants record themselves answering questions, may evoke creepiness as they interact with software rather than a human representative. While these technologies are not as widespread as videoconferencing interviews, they garner significant interest among organizations, signifying their growing adoption in the recruitment process. With increased familiarity and usage, the perceived creepiness associated with digital interviews may decrease. The lack of "real" social interaction could induce feelings of creepiness (Langer et al., 2017; Langer & König, 2018)

The creepiness scale, consisting of 10 items, will be adopted from (Langer & König, 2018). The scale comprises two facets, namely emotional creepiness and creepy ambiguity, each measured with five items. A sample item for emotional creepiness is “During the shown situation, I had a queasy feeling,” while a sample item for creepy ambiguity is “I did not know how to judge this situation.”

3.10.3 Perceived Validity, Accuracy, and Trust

Perceived validity, in this context, pertains to the user's evaluation of the trustworthiness and accuracy of the information provided by AI tools (Chan et al., 1998). This thesis assesses perceived validity across three main aspects. Firstly, we evaluate the perception of AI tools to generate precise and comprehensive job descriptions, ensuring they accurately capture the necessary job requirements and responsibilities. Secondly, we measure perceived validity in the context of AI's ability to collect data from applicant tests and accurately predict an applicant's potential job performance based on these test results. This involves evaluating whether applicants perceive AI's capacity to effectively gauge their suitability for a job based on their test performance. Lastly, we assess perceived validity by evaluating the accuracy and reliability of information provided by AI in interactions with it. This aspect explores how users perceive the AI output in terms of credibility and trustworthiness.

To assess trust, we draw inspiration from (Köchling et al., 2021), whose work delves into the effects of AI-based selection processes on applicant responses and organizational attractiveness. We also consider Bauer's research, which examines perceived corporate reputation and customer outcomes based on factors like satisfaction, loyalty, trust, and word-of-mouth. In line with Lee & See, (2004), trust is viewed as the belief that an agent will help an individual achieve their goals in situations marked by uncertainty and vulnerability. Trust hinges on reliability, honesty, and integrity. Job seekers may view AI use in recruitment as more ethical, and organizations as trustworthy, if AI is used for performance related purposes, and if organizations are transparent with its use (Figueroa-Armijos et al., 2023). In Chapter 2, ethical challenges associated with utilizing AI in recruitment are discussed. AI systems, designed based on historical employment data, may inherently exhibit discriminatory biases, particularly in areas such as race and gender (Noble et al., 2021). The limited accessibility to the proprietary code of AI tools, coupled with the lack of control HR managers have over their design in recruitment, underscores the necessity of examining how individuals perceive organizations using AI and whether they find them credible and trustworthy. Conversely, AI's purported accuracy and objectivity might lead to blind trust (Leicht-Deobald et al., 2019). Even when it is difficult to understand how AI processes, an organization can still be seen as trustworthy, if the outcome is effective and aligns with the user (Figueroa-Armijos et al., 2023; Gonzalez et al., 2022; Lacroux & Martin-Lacroux, 2022).

We aim to gauge users' perception of an AI tool's trustworthiness at different stages of the recruitment process. Perceived validity measured on a five-point Likert scale measured ranging from 1 (strongly disagree) to 5 (strongly agree), using two items of predictive validity perceptions from (Chan et al., 1998). A sample item is “I am confident that the test can predict how well an applicant will perform on the job.”

3.10.4 Privacy Concern

During the application and recruitment processes, applicants often find themselves disclosing sensitive and personal information. This situation raises concerns about the privacy and security of their data, especially when these processes involve new technologies, online platforms, or automated methods (Bauer et al., 2011; Langer et al., 2017). Applicants may express unease regarding the accessibility and potential misuse of their confidential documents, images, videos, or recorded interviews. The fear of third parties gaining access to sensitive information about the applicant intensifies these privacy concerns (Bauer et al., 2011; Langer et al., 2017).

Data security and privacy are of paramount importance in e-recruitment, particularly concerning the safeguarding of applicant information (Chuks Okolie & Irabor, 2017; Omolawal, 2015). The successful integration of AI tools into the recruitment process hinges significantly on candidates' perceptions of AI usage. Therefore, it is essential to consider candidates' viewpoints and provide assurances concerning the privacy and security of these tools (Lundvall, 2022). Transparency about the use of AI technologies during recruitment can enhance safety and neutrality, effectively addressing candidates' privacy concerns (Lundvall, 2022). Candidates' perceptions of privacy play a pivotal role as their discomfort or lack of trust in these tools might deter them from applying or continuing with the application process, which could potentially lead to a loss of valuable candidates for companies. Likewise, creepiness perceptions will be present in situations where there are privacy concerns (Langer & König, 2018).

One of the significant challenges when integrating AI into recruitment processes is the establishment of privacy and ethical practices (Black & van Esch, 2020; Lundvall, 2022). It is highly recommended to conduct a thorough exam of the impacts, strengths, and weaknesses of AI systems before implementing them in recruitment processes (Lundvall, 2022; Omolawal, 2015). This study aims to explore the current perspectives of recruiters, applicants, and AI experts regarding privacy concerns associated with the use of AI tools in recruitment. Addressing these privacy concerns involves promoting transparency and openness regarding the utilization of AI tools in the recruitment process, as suggested by Nawaz & Gomes, (2020). In our scenarios, we provide specific details on how AI tools are employed at each step, avoiding excessive algorithmic explanations, with the intention of examining whether transparency can mitigate privacy concerns. Privacy concerns will be measured with six items. Items from Malhotra et al., (2004), two items from Langer and colleagues (2018), and one item from (Langer et al., 2017). A sample item is “Situations like the one shown threaten participants’ privacy”, see Appendix A.

3.10.5 Fairness

Perceptions of fairness in AI-based recruitment pertain to how individuals assess the fairness of decision-making processes and outcomes driven by AI. Fair applicant treatment is important for organizational views, especially when targeting high-quality candidates in the war for talent. Organizations must increase their efforts to present themselves positively to qualified candidates, recognizing that perceived fairness of the recruitment process plays a pivotal role in shaping individuals' intention to accept a job offer, in other words organizational attractiveness (Warszta, 2012). Concerns about fairness often emerge due to algorithmic bias and a lack of transparency in AI systems (Ochmann & Laumer, 2019). The risk of perpetuating biases from historical data exists in AI algorithms, potentially resulting in unfair outcomes (Noble et al., 2021). Conversely, human recruiters may introduce biases based on personal beliefs or stereotypes. AI presents an advantage in mitigating some of these biases by making decisions grounded in objective criteria and predefined algorithms, which consistently follow the same procedures and remain unaffected by emotional factors (M. K. Lee, 2018).

Despite these advantages, the lack of transparency in AI decision-making can impact fairness perceptions, leading applicants to question the objectivity of the process. Prior research has produced mixed findings on fairness perceptions, with some studies suggesting no significant difference in fairness ratings between human and AI recruiters (refer to Table 3.2). However, factors such as the level of transparency regarding evaluation processes can influence perceived fairness in AI-based recruitment. Fairness heuristic theory for selection suggests that procedural justice, which pertains to the fairness of the selection process, is influenced by how applicants perceive the selection system and its fairness (Schinkel et al., 2013). Procedural justice refers to applicants' perception of fairness, ensuring that the decision-making process in hiring is unbiased and just (Colquitt, 2001; Gilliand, 1993). In the context of this thesis, procedural justice plays a crucial role in how applicants perceive an organization's decision-making during the selection process. This study aims to present concise scenarios illustrating how AI could be integrated into recruitment processes. It seeks to compare the perspectives of recruiters, applicants, and AI experts' perceptions of fairness. Fairness will be assessed using two items adapted from Warszta (2012), with a sample item being, "I think the shown procedure is fair."

Table 3.2 Papers assessing the fairness perceptions of AI in recruitment. This table was taken directly from (Will et al., 2022)

Citation	**Key finding(s)**	**AI better worse or equal to human recruitment methods in fairness perceptions**
(Suen et al., 2019)	Applicants had indistinguishable fairness ratings between human and AI hiring methods	Equal
Newan et al. (2020)	In a low transparency condition, algorithmic hiring was perceived as fairer than humans	Better

Newan et al. (2020)	In a high transparency condition, algorithmic hiring was perceived as less fair than humans	Worse
(M. K. Lee, 2018)	Algorithmic hiring decisions found to be viewed as less fair than human hiring decisions	Worse
(Acikgoz et al., 2020)	AI interviews rated lower on procedural justice and interactional justice compared to human interviews	Worse
(Noble et al., 2021)	AI interviews rated lower on procedural justice and interpersonal justice compared to human interviews	Worse
(Warrenbrand, 2021)	AI hiring rated lower on distributed and procedural justice than human hiring	Worse
Langer et al. (2018)	No difference in fairness ratings in algorithmic hiring conditions with low or high information given	Unclear
(Kodapanakkal et al., 2020)	Data protection found to be strongest driver of moral acceptability of algorithms	Unclear
(Langer et al., 2019)	No difference in candidate fairness ratings between AI and human interviews	Equal
(Bigman et al., 2022)	Participants are less outraged by hiring discrimination from an algorithm than from a human. Participants attribute higher prejudiced motivation to humans than algorithm decision makers. The attribution of bias mediates the effect of discrimination on moral outrage	Better

3.10.6 Opportunity to Perform.

Opportunity to perform, a facet of perceived fairness, is linked to applicants' perceptions of their ability to effectively showcase their skills, knowledge, and abilities during AI-assisted tests or interviews. This concept is closely tied to the growing trend of organizations utilizing machine learning and deep learning techniques to automatically evaluate applicants' performance in various contexts. Companies are increasingly using these techniques to assess applicants during interviews, considering factors such as nonverbal cues (e.g., smiling, nodding) and verbal communication (e.g., word choice) (Barocas & Raghavan, 2019). By utilizing items from Warszta (2012) (see Appendix A), we aim to explore how users perceive their opportunities to display their capabilities through AI-assisted assessments. Our goal is to understand whether users believe these AI tools provide a fair chance to exhibit their skills.

It's important to note that some users may assume that replacing human raters with AI can reduce biases often associated with performance evaluations, including racial biases (Segrest Purkiss et al., 2006). However, it is crucial to recognize that AI tools may not always be inherently less biased than humans. To clarify, our focus is not on evaluating the technical effectiveness of computer models or factors like screen size on performance. Instead, we aim to understand users' perceptions of the opportunity to demonstrate their skills through AI-driven methods in a general sense. We are interested in whether users feel they have had a fair chance to showcase their abilities and skills, rather than directly assessing AI's ability to measure their skills. This variable was measured with three items from (Bauer et al., 2011), e.g., “This application process gives applicants the opportunity to show what they can really do.”

3.10.7 Two-way Communication

The interpersonal dynamics between recruiters and applicants play a crucial role in shaping applicant perceptions. Interactional Justice is a concept that relates to the quality of interactions between applicants and test administrators. It encompasses elements such as displaying warmth and respect towards applicants and ensuring they have the opportunity to ask questions or voice concerns (Acikgoz et al., 2020). Research indicates that applicants respond less positively to selection procedures perceived as less personal (Laurim et al., 2021; M. K. Lee, 2018). AI systems have the ability to facilitate communication relationships between candidates and recruiters or the company (Upadhyay & Khandelwal, 2018).

Langer et al., (2017) found that asynchronous digital interviews were perceived to have less two-way communication and poorer interpersonal treatment compared to live video-conference interviews, emphasizing the importance of two-way communication. Acikgoz et al. (2020) discovered significant positive relationships between two-way communication and organizational attractiveness. Two-way communication during the application process allows applicants to express their opinions, provide input, ask questions, and have their contributions acknowledged and considered during the selection process. Two-way communication is positively associated with organizational attractiveness (Acikgoz et al., 2020).

In the context of this thesis, the assessment of two-way communication focuses on evaluating the level of comfort experienced by applicants during chatbot conversations. Job seekers actively seek information about companies and job roles, with this information provision being deemed critical in the recruitment process. The quantity and quality of information provided directly impacts the user experience of applicants (Sylva & Mol, 2009). Consequently, the scenario included in this study aims to facilitate discussions between applicants and the chatbot regarding organizational and job-related information. Through this scenario, our objective is to determine whether users feel inclined and at ease when asking questions or engaging in conversations with the chatbot on these topics. This is measured by items from (Bauer et al., (2011) and Warszta (2012)such as “I would have felt comfortable asking questions about the interview if I had any.”

3.10.8 TAM & Perceived Usefulness

The Technology Acceptance Model (TAM) stands as a widely employed theory, offering a framework for evaluating the acceptance or rejection of information systems, particularly pertinent to AI in the recruitment process (Laurim et al., 2021; Natasia et al., 2022). Originally proposed by Davis in 1989, TAM considers various factors such as perceived usefulness, perceived ease of use, and intention of use.

This paper focuses on perceived usefulness, capturing the user's perspective on the extent to which AI tools prove advantageous in the recruitment process. Perceived Usefulness, in this context, relates to the likelihood of job application. It strongly motivates individuals to use technology, as AI may provide significant benefits for job seekers (Chen, 2022). The use of AI must inherently offer value and bring motivation or perceived enjoyment to candidates (van Esch et al., 2019).

One of the study's objectives is to assess users' perceptions regarding the usefulness and potential creepiness associated with AI tools in recruitment. While AI-powered application filtering enhances time and cost efficiency for recruiters and companies, it also has the potential to elicit feelings of creepiness among applicants. This may lead to decreased application rates and a reduced pool of potential employees. It is crucial to investigate whether users view this recruitment method as beneficial and useful. Even when users find a tool useful, its implementation may still induce feelings of creepiness, impacting user adoption. The aim is to evaluate whether the perceived benefits of this AI-based recruitment method outweigh the potential creepiness and distrust it may evoke among users. This evaluation is measured using self-developed items, such as "The mode of communication benefits me." Please refer to Appendix A for all scales and items.

3.10.9 Satisfaction

Perceived satisfaction is influenced by various factors, including perceived fairness, user-friendliness, and efficiency (Sylva & Mol, 2009). This study specifically focuses on assessing overall process satisfaction to determine whether users, including AI experts, applicants, and recruiters, are content with the integration of AI tools at specific stages of the recruitment process. By evaluating this aspect, we aim to gain insights into the impact of AI implementation on user satisfaction levels. Fairness perceptions are closely tied to satisfaction with the application process and can influence recommendations (organizational attractiveness) (Sylva & Mol, 2009; Warszta, 2012). Perceived satisfaction refers to the value a user perceives they have received in relation to a product or service based on their evaluation of its worth. Individuals who perceive unfair treatment may experience decreased commitment to accepting a job offer and reduced job satisfaction. Additionally, they may discourage others from applying to a role, diminishing organizational attractiveness (Lavanchy et al., 2023). Furthermore, user satisfaction with the selection process can influence their perceptions of the fairness of the entire selection process (Nikolaou & Georgiou, 2018). Satisfaction will be evaluated using three items adapted from Sylva & Mol (2009), with a sample item being, "Overall, I was satisfied with this job description development process."

Chapter 4: Findings & Discussion

4.1 General Findings

E-recruitment, specifically AI-recruitment, is an emerging trend (van Esch et al., 2019). Its current applications are in the initial phases of the recruitment process. There is little information on insights into the reactions of job seekers and HR executives toward AI-powered hiring processes (Laurim et al., 2021; van Esch et al., 2019). Despite the substantial advancements in AI technology within the HR domain and the investments that have been made in developing software and refining algorithms to match job requirements with potential candidates (Horodyski, 2023b). Furthermore, the existing body of research on artificial intelligence in the recruitment process remains relatively limited with few studies addressing this specifically (see: Hilliard et al., 2022).

HR practitioners should acknowledge that the adoption or rejection of AI-driven recruitment processes may create divides among various stakeholders, such as job applicants and organizations. Such divisions could potentially impact relationships within communities, networks, and virtual interactions (Lepak & Snell, 1998), specifically organizational views. Furthermore, these outcomes may carry adverse effects, considering that technology heavily relies on candidate motivation—an essential element for the effectiveness of human resource management in the recruitment of candidates (van Esch et al., 2019).

Adverse and negative perceptions towards organizations can have detrimental impacts, deterring potential applicants from applying or engaging with the organization's products or services. Therefore, it is essential to understand the perceptions of applicants regarding AI in recruitment. Integrating candidate experiences and perspectives with e-recruitment technologies can significantly enhance the effectiveness of AI recruitment tools and processes. Similarly, it is crucial to comprehend the feelings and opinions of recruiters, who directly engage with these technologies, and AI experts, who possess in-depth knowledge about these technologies. Understanding their perspectives can offer valuable insights into optimizing AI-driven recruitment practices.

To address our second research question, we sought to gauge participant perceptions regarding AI implementation at different stages of the recruitment process. To achieve this, we developed eight distinct scenarios, each outlining a specific utilization of AI technology at a particular phase of the recruitment process. These scenarios were designed to depict varied instances of AI application, enabling us to assess participant reactions and attitudes towards AI integration across multiple stages of recruitment. Through this method, we aimed to capture an understanding of how individuals, particularly AI experts, applicants, and recruiters, perceive and respond to AI's involvement at different stages within the recruitment process.

Quantitative data from the survey were analyzed using appropriate statistical methods. Descriptive statistics, including means and standard deviations, were used to summarize participants' ratings. Inferential statistics, such as Analysis of Variance (ANOVA), were employed to examine differences among the user groups and the influence of AI knowledge on perceptions. T-tests were not used as they can measure two group differences, not three, such as in our study.

To restate our research questions and summarize our key results, we found that:

RQ2: What are the perceptions of participants (applicants, AI experts, and recruiters) regarding the use of AI at each stage of the recruitment process?

- Regardless of the stage at which AI is implemented in the recruitment process, respondents had neutral to positive organizational perceptions.
- In scenario 1 (S1), participants expressed satisfaction, harbored positive perceptions of fairness, perceived validity, and found the organizational attractiveness to be high. Recruiters reported low levels of creepiness perceptions, while AI experts and applicants exhibited neutral to negative perceptions of creepiness.
- In Scenario 2 (S2), participants reported satisfaction and held positive views regarding organizational attractiveness and fairness. Additionally, participants expressed neutral to positive perceptions of the validity of the AI tool employed in S2, while demonstrating low levels of privacy concerns and emotional creepiness associated with the ATS.
- In Scenario 3 (S3), AI experts exhibited positive perspectives on perceived fairness, opportunity to perform, and satisfaction. All participants, including AI experts, displayed positive organizational perceptions, and demonstrated close to neutral mean scores regarding privacy concerns. However, applicants expressed lower perceptions on the chance to perform and validity, accompanied by feelings of creepiness and neutral satisfaction. Recruiters, on the other hand, viewed chance to perform, validity, and creepiness at neutral levels.
- In scenario 4 (S4), participants across all roles exhibited close to neutral mean scores in their assessments of perceived fairness, chance to perform, validity, satisfaction, and privacy. However, regarding perceptions of creepiness (S4.5), AI experts expressed a discomfort level with a mean of 3.53, while applicants and recruiters demonstrated a more neutral mean score.
- In scenario 5 (S5), participants across all roles exhibited close to neutral mean scores in their assessments of perceived fairness, validity, satisfaction, creepiness, organizational attractiveness, and privacy. However, in the context of perceived chance to perform measure (S5.2), AI experts expressed a mean score of 3.37, while applicants and recruiters expressed slightly lower mean scores of 2.57 and 2.82, respectively.
- In scenario 6 (S6), participants across all roles exhibited close to neutral mean scores in their assessments of perceived fairness, validity, satisfaction, and creepiness. Notably, participants express neutral to positive perceptions regarding organizational attractiveness. However, concerning perceived privacy (S6.6), applicants indicated a higher level of privacy concern with a mean score of 3.77, while AI expert and recruiters show averages of 3.11 and 3.53, respectively.
- In scenario 7 (S7), participants across all roles exhibit neutral to positive mean scores in their assessments of perceived two-way communication (S7.1), organizational attractiveness (S7.3), satisfaction (S7.5), benefit-usefulness (S7.6), and validity (S7.7).

Notably, regarding perceptions of creepiness, recruiters' rate S7 as less creepy compared to applicants and AI experts, with mean scores of 2.82, 3.30, and 3.37, respectively. Additionally, applicants express higher privacy concerns than AI experts and recruiters, registering mean scores of 3.70, 2.95, and 3.24, respectively.

- In scenario 8 (S8), participants across all roles exhibit close to neutral mean scores in their assessments of perceived emotional creepiness (8.2), organizational attractiveness (S7.3), and privacy (S8.4). Participants positive perceptions of two-way communication (S8.1), satisfaction (S8.5), benefit-usefulness (S7.6), and validity (S7.7).

These findings are based on means (see tables in section 4.2 through 4.8 for data points).

RQ3: Do the perceptions of applicants, AI experts, and recruiters differ with the integration of AI in various recruitment stages?

- There was no significant difference among the perceptions of applicants, AI experts, and recruiters in S1 for measures S1.1, S1.2, S1.3, and S1.4.
- A significant difference was observed in measure S1.5, among AI experts, applicants, and recruiters, as indicated by the three-way ANOVA test with a p-value of 0.005.
    - Kruskal-Wallis test reveals significant differences in S1.5 scores in post hoc analysis between the applicant (mean rank= 66.10) and recruiter (mean rank=46.59) groups (p=0.019) and the AI expert (mean rank=74.47) and recruiter (mean rank=46.59) groups (p=0.013). However, there was no significant difference between the AI expert (mean rank=74.47) and applicant (mean rank= 66.10) groups, with a p-value of 1.000. Recruiter showed lower S1.5 compared to the other groups. See table 4.2.
- There was no significant difference among the perceptions of applicants, AI experts, and recruiters in S3 for measures 3.1, 3.4, 3.6, and 3.7.
- A significant difference was found using ANOVA, between AI experts, applicants, and recruiters was observed in measure S3.2 (p=0.026), S3.3 (p=0.024), and S3.5 (0.036).
    - A Kruskal-Wallis post hoc analysis S3.5 scores showed no statistically significant difference between any of the roles.
    - A Kruskal-Wallis post hoc analysis S3.3 scores showed only a statistically significant difference between applicant (mean rank=57.74) and recruiter (mean rank=67.65), (p=0.030).
    - A Kruskal-Wallis post hoc analysis S3.2 scores showed only a statistically significant difference between applicant (mean rank=58.86) and AI experts (mean rank= 71.82), (p=0.041).
- ANOVA results indicate a statistically significant difference in participants' perceptions of S5.2 The p-value of 0.035 is less than the chosen significance level (e.g., 0.05), suggesting a significant difference in perceptions among the roles.
    - A Kruskal-Wallis post hoc analysis revealed statistically significant differences in S5.2 scores between the applicant (mean ran=56.51) and AI expert (mean rank=79.82), (p=0.028), but not any other groups.

- S7 ANOVA results indicate a statistically significant difference in participants' perceptions of S7.6 but no other measures, among the AI Expert, Applicant, and Recruiter. The p-value of 0.010 is less than the chosen significance level (e.g., 0.05), suggesting a significant difference in perceptions among the roles.
    - A Kruskal-Wallis post hoc analysis revealed statistically significant differences in S7.6 scores between the applicant (mean rank= 69.41) and AI expert (mean rank=46.71), (p=0.029), but not between any other groups.
- There was no significant difference among the perceptions of applicants, AI experts, and recruiters in S2, S4, S6, and S8.
- Video gaming habits are positively associated with higher and positive perceptions of fairness, satisfaction, perceived opportunity to perform, organizational attractiveness and lower creepiness perceptions than those who do not play video games often in S5.

RQ4: How does the potential integration of AI in various recruitment stages impact users' perception of fairness at each stage?

- The trend of fairness perceptions across all roles shows a decline from S1 to S5, followed by an increase from S5 to S6, as illustrated in Figure 4.1.
- AI experts demonstrate similar perceptions of fairness compared to both applicants and recruiters. Our analysis indicates that there are no significant differences in the perception of fairness across the various stages (S1-S6) of the recruitment process for AI. See table 4.1. for ANOVA results of p values.
- Participants across all roles exhibit positive fairness perceptions for S1, and S2.
- Participants across all roles exhibit neutral fairness perceptions for S4, S5, and S6 with large standard deviations meaning that.
- AI experts exhibited a higher perceived fairness in S3.1 with a mean score of 3.47, compared to applicants and recruiters who reported mean scores of 2.91 and 2.97, respectively. An ANOVA test indicates that there are no significant differences among these perceptions, with a p-value of 0.140. While there is a numerical difference in the mean scores, the statistical test suggests that this difference may not be considered statistically significant at the chosen level of significance (set at 0.05).

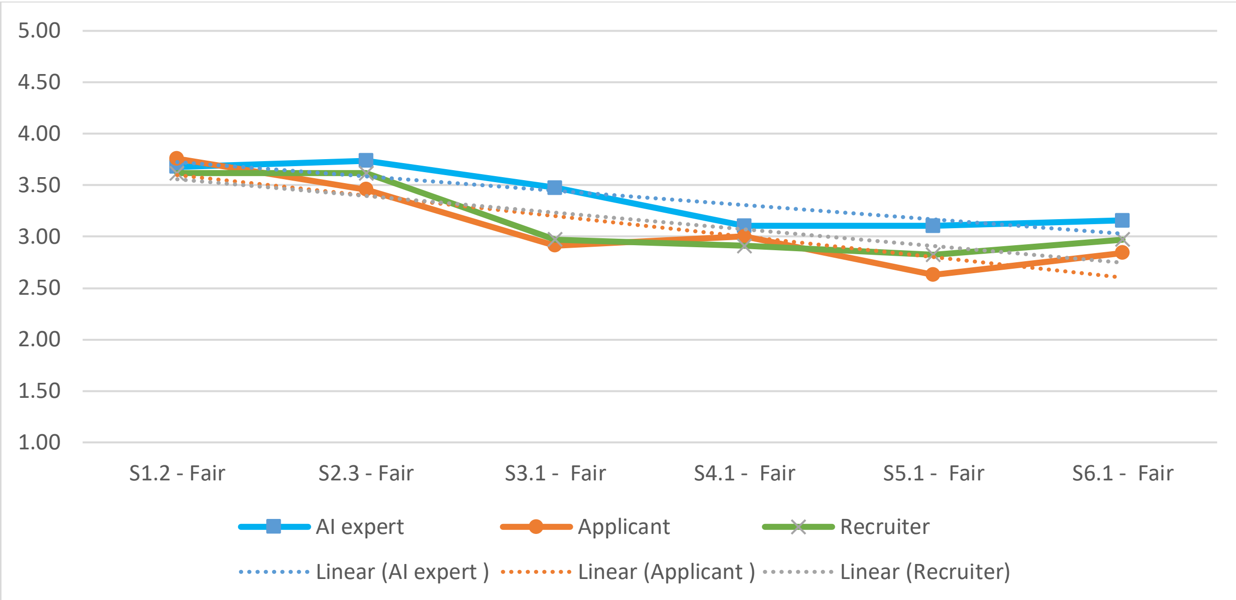

Figure 4.1: Trend of Fairness Perceptions: Mean Scores Across S1 to S6 for AI Experts, Applicants, and Recruiter

Table 4.1 Three-way ANOVA test for fairness perceptions in S1 through S6, values retrieved from data with IBM SPSS

Scenario	Variation	Sum of squares	Degrees of Freedom	Mean square	F	Significant difference (p-value)
S1	Between Groups	.457	2	.229	.302	.740
	Within Groups	91.006	120	.758		
	Total	91.463	122			
S2	Between Groups	1.419	2	.710	.859	.426
	Within Groups	99.085	120	.826		
	Total	100.504	122			
S3	Between Groups	4.774	2	2.387	2.001	.140
	Within Groups	143.193	120	1.193		
	Total	147.967	122			
S4	Between Groups	.467	2	.234	.175	.840

	Within Groups	160.525	120	1.338		
	Total	160.992	122			
S5	Between Groups	3.609	2	1.805	1.196	.306
	Within Groups	181.074	120	1.509		
	Total	184.683	122			
S6	Between Groups	1.573	2	.787	.587	.558
	Within Groups	160.768	120	1.340		
	Total	162.341	122			

In the following sub-sections, we detail the results of our survey pertaining to the use of AI in different stages of the recruitment process.

4.2 AI in Description, S1

AI can be used in the description phase to write, edit, upload and update job descriptions (Rab-Kettler & Lehnervp, 2019). Ascertaining hiring needs is the first major challenge of the recruitment process (Holm, 2012). This includes identifying roles, qualifications, experience level, and skills required to write in the job description. S1 describes how AI can be implemented in this step. The finding indicates participants irrespective of their role (applicant, AI expert, recruiter) had positive views on organizational attractiveness (p=0.987), perception of satisfaction (p=0.730), fairness (p=0.740) and validity (p=0.918) with no significant difference among roles. Refer to Table 4.2 and Figure 4.2 for mean perceptual values of S1.

The ANOVA results reveal a statistically significant difference in participants' responses to the statement "During this situation, I felt uncomfortable" across the different roles (AI Expert, Applicant, and Recruiter), p=0.005. This statement measured perceptions of creepiness (S1.5). As mentioned before, creepiness is defined as an “unpleasant affective impression elicited by unpredictable people, situations, or technologies” (Langer & König, 2018, p. 2), in this case technologies, specifically AI. The p-value of 0.005 is less than the chosen significance level (e.g., 0.05), indicating that there is a significant difference in perceived discomfort levels among the roles. A Kruskal-Wallis H test was run to determine if there were differences in S1.5 score between three groups of participants with different roles: the "AI expert" (n=19), "applicant" (n=70), and "recruiter" (n=34) role groups. Values are mean ranks unless otherwise stated. Distributions of creepy scores were not similar for all groups, as assessed by visual inspection of a boxplot. The mean ranks of S1.5 scores were statistically significantly different between groups, the distributions of S1.5 scores were statistically significantly different between groups, $\chi2(2) = 10.498$, p = 0.005. Subsequently, pairwise comparisons were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons. Adjusted p-values are presented.

Values are mean ranks unless otherwise stated. This post hoc analysis revealed statistically significant differences in S1.5 scores between the applicant (mean rank=66.10) and recruiter (mean rank= 46.59), (p=0.019) group and the AI expert (mean rank=74.47) and recruiter (mean rank= 46.59), (p=0.013), but not between the AI expert (mean rank=74.47) and applicant (mean rank=66.10), (p=1.000).

The study's results indicate that recruiters tend to be more comfortable and find it less creepy to use AI in the recruitment process compared to both applicants and AI experts. One plausible explanation for this trend could be attributed to the recruiters' professional exposure and familiarity with various tools and technologies in the recruitment domain. Recruiters, by their role, are likely to have regular exposure to technology-driven solutions in the recruitment landscape. Their professional experience makes them accustomed to utilizing AI for tasks such as writing, editing, and updating job postings. Additionally, recruiters possess expertise in crafting job descriptions, understanding the nuances of language, tone, and content that resonate with potential candidates. If recruiters perceive that AI can enhance the performance of routine tasks and improve efficiency without compromising quality, they may view AI positively (Ore & Sposato, 2021) . One participant, a recruiter (Participant 122), explicitly expressed a preference for AI over humans in writing job descriptions, stating,

"Honestly, I would prefer AI rather than a human to write the job descriptions."

This sentiment aligns with the idea that recruiters may find AI useful in tasks they are already familiar with, viewing it as a potential time-saving tool in the job description creation process.

Table 4.2: Mean and Standard Deviation (SD) Values of Measures Across AI Experts, Applicants, and Recruiters for Stage S1

	AI Expert		**Applicant**		**Recruiter**	
Survey Question	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
S1.1- Organization	4.11	0.46	4.07	0.97	4.09	0.75
S1.2 - Fair	3.68	1.00	3.76	0.86	3.62	0.82
S1.3 - Satisfied	3.89	0.74	3.73	0.83	3.74	0.86
S1.4 - Validity	3.68	0.96	3.67	0.83	3.65	0.88
S1.5 - Creepy	2.89	1.05	2.60	1.11	2.03	0.83

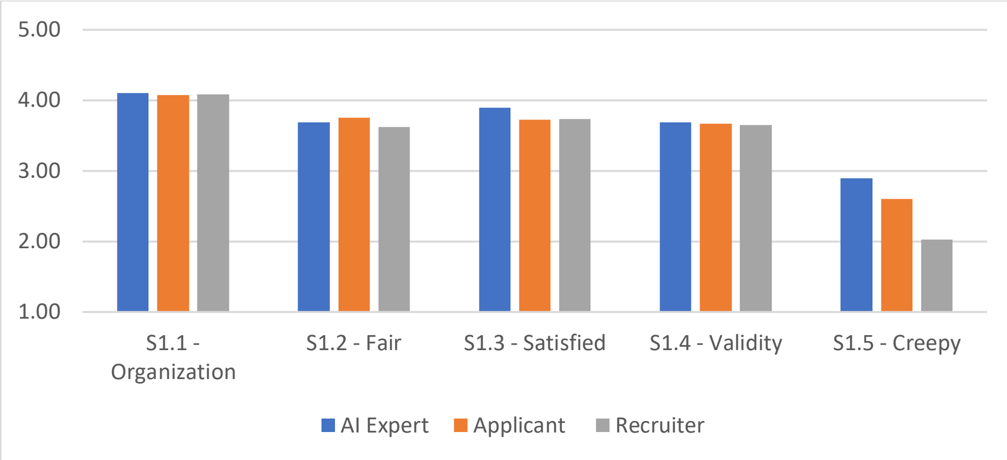

Figure 4.2: Perceptual Insights- Mean Values across S1.1 to S1.5 for AI Experts, Applicants, and Recruiters

4.3 AI in Sourcing and Attraction, S2

The attraction phase in recruitment serves the purpose of maximizing both the size and quality of the applicant pool (Chapman & Gödöllei, 2017). This step, being the second major phase in the recruitment process, traditionally involved methods such as job boards and newspaper articles. The advent of e-recruitment ushered in online access to attract participants. In the realm of AI-recruitment, this process extends further, engaging with talent across various platforms such as web, mobile, and social channels. AI, through these interactions, gains insights into talents, values, beliefs, and attitudes, thereby accessing a larger talent pool and personalizing the applicant experience (Upadhyay & Khandelwal, 2018). One significant application of AI in this context is through ATS integrated with AI technology. These systems effectively match applicants with job opportunities based on their resume and application history. The practical implementation of this use-case is exemplified in S2. This integration is meant to streamline the process for recruiters and enhance the efficiency of connecting qualified applicants with suitable job opportunities, contributing to the overall effectiveness of the attraction phase in the recruitment journey. Refer to Table 4.3 and Figure 4.3 for mean perceptual values of S2.

The survey findings reveal consistent positive views across all roles (applicant, AI expert, recruiter). The participants held positive views regarding fairness perceptions (p=0.426), organizational attractiveness (p=0.780), privacy (p=0.479), satisfaction (p=0.713), validity (p=0.090), and creepiness (0.586). There was no significant difference among perceptions, indicating a consensus across participants, aligning with the findings in D6. Participants demonstrated confidence in AI for personalized decision-making. This shared confidence could explain the results observed in S2, where AI is used to personalize and attract applicants based on predetermined information. The confidence expressed by all participants in AI for personalized decision-making likely contributes to a positive and unified perception of AI's role in tailoring the recruitment process. The personalized decision-making capabilities of AI, as reflected in S2, may resonate well with participants who have confidence in AI's ability to handle similar tasks effectively. Contributing to higher satisfaction, fairness, and organizational perceptions.

Another explanation could be outcome favorability, which gauges the personal benefit of a technology's outcome for the decision-maker, regardless of fairness to others, influences technology adoption (Krehbiel & Cropanzano, 2000). Studies suggest that positive procedural justice perceptions arise from favorable outcomes. In the scenario provided to the participants, ATS was used to identify an ideal candidate. Based on the description it was implied that the participants were the candidates which may lead them to view themselves favorably as potential ideal candidates, thus influencing positive perceptions of procedural justice. Research demonstrates that positive outcomes are often perceived as fair, whereas unfavorable outcomes tend to be seen as unfair (Krehbiel & Cropanzano, 2000). The positive association between favorable outcomes generated by computer algorithms and perceived fairness adds further validation to this perception (Lavanchy et al., 2023). Participant 12 affirmed this perspective, expressing agreement that ATS sourcing might be perceived as creepy but is beneficial if the outcome is favorable to them. They conveyed,

"I mean it's a little creepy, but if I get the job, I wouldn't mind if they approach me with ATS. It helps me save a step and not have to go out of my way to look for that job or role."

Participant 12's response reflects a pragmatic perspective, acknowledging the potential creepiness of the technology while also recognizing the practical benefits it offers. The emphasis on the positive outcome, such as securing a job opportunity more efficiently, appears to outweigh the initial discomfort associated with the perceived creepiness. This aligns with the idea that favorable outcomes generated by computer algorithms can influence and shape perceptions of fairness in the recruitment process. While some participants expressed privacy concerns, the majority did not share these concerns See table 4.3.1 for mean values of each measure in S2. Overall, participants were satisfied with the ATS-aided attraction process. However, studies have indicated that unfavorable outcomes can lead to negative views and decision-making concerning AI systems (Lavanchy et al., 2023). These findings underscore the impact of positive outcomes on perceptions of fairness and the importance attached to privacy concerns in technology adoption (Kodapanakkal et al., 2020). Research showed that employment-related technologies intruded on individuals' privacy to some extent, resulting in reported discomfort or feelings of being "creeped out" by these technologies but people would still choose to accept the technologies rather than reject it entirely (Kodapanakkal et al., 2020). Similarly, we found that some participants were “creeped” out, but all showed high organizational attractiveness. The results warrant additional investigation.

Table 4.3: Mean and Standard Deviation (SD) Values of Measures Across AI Experts, Applicants, and Recruiters for Stage S2

	AI Expert		**Applicant**		**Recruiter**	
Survey Question	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
S2.1 - Organization	4.16	0.76	4.04	0.65	4.09	0.57
S2.2 - Satisfied	3.84	0.90	3.67	0.77	3.71	0.80
S1.3 - Fair	3.74	0.99	3.46	0.91	3.62	0.85
S2.4 - Validity	3.53	0.96	2.91	1.10	3.12	1.09

S2.5 - Creepy	2.79	1.18	2.51	0.97	2.56	1.05
S2.6 - Privacy	2.89	1.29	2.83	1.14	2.56	1.19

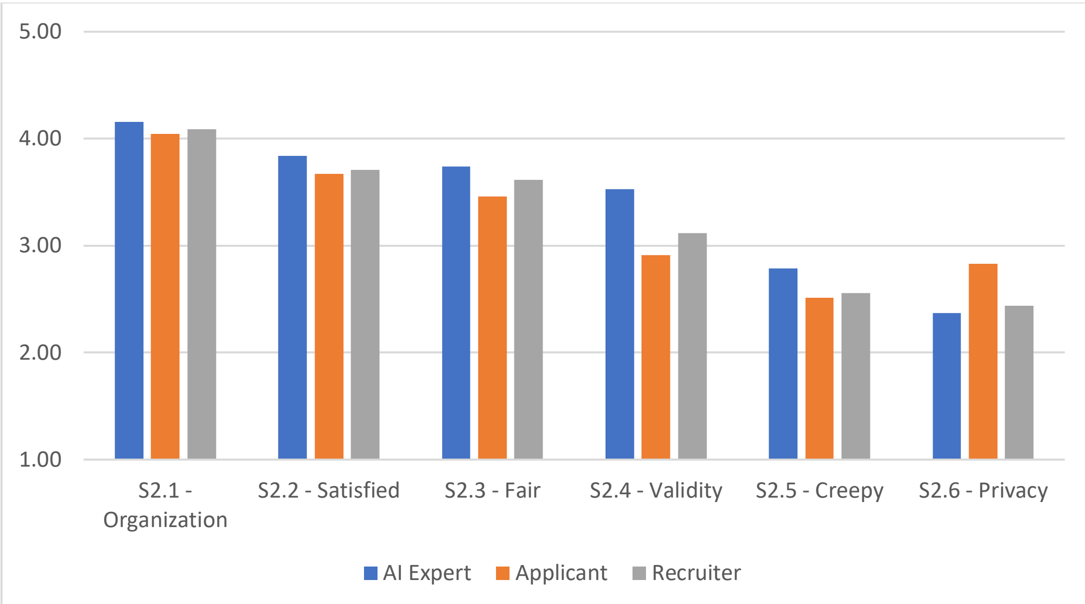

Figure 4.3: Perceptual Insights- Mean Values across S2.1 to S2.6 for AI Experts, Applicants, and Recruiters

4.4 AI in Screening, S3

Screening is the process in which the available information regarding candidates is screened and sorted. Resume screening is completed by statistical measures that include analyzing the meaning of the words, search for keywords or phrases, and grammar checks. ATS the ability to prescreen applications. And placing candidates in the right job openings (Rab-Kettler & Lehnervp, 2019). Resume screening is already popular among organizations, 98% of fortune 500 companies already use ATS to pre-filter resumes. Refer to Table 4.4 and Figure 4.4 for mean perceptual values of S3.

A Kruskal-Wallis H test was run to determine if there were differences in creepiness (S3.5) score between three groups of participants with different roles: the "AI expert" (n=19), "applicant" (n=70), and "recruiter" (n=34) role groups. Values are mean ranks unless otherwise stated. Distributions of creepy scores were not similar for all groups, as assessed by visual inspection of a boxplot. The mean ranks of S3.5 scores were statistically significantly different between groups, the distributions of S3.5 scores were statistically significantly different between groups, $\chi2(2) = 6.734$, $p = 0.034$. Subsequently, pairwise comparisons were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons. Adjusted p-values are presented. Values are mean ranks unless otherwise stated. This post hoc analysis revealed no statistically significant differences in S3.5 scores between the applicant (mean rank= 62.59) and recruiter (mean rank=56.60), (p=0.100), applicant (mean rank= 62.59) and AI expert (mean rank=69.47), (p=0.139), and the AI expert (mean rank=69.47),) and recruiter (mean rank=56.60), (p=1.000).

In essence, while there is an overall significant difference in the distributions of S3.5 scores among the three role groups, the post hoc tests suggest that the pairwise differences between specific roles are not statistically significant after applying the Bonferroni correction. This could mean that, despite an overall difference, it's challenging to pinpoint exactly which pairs of roles are significantly different from each other based on S3.5 scores. Interpreting these findings should consider the context of the S3.5 scores and the specific aspects of workplace scenario or AI application under investigation. Additionally, the lack of significance in pairwise comparisons could indicate that, for this particular measure, the perceptions of applicants, AI experts, and recruiters are relatively similar. This is confirmed by the median results.

Based on chart representations, we find that applicants find AI's use in this step creepy, whereas AI experts find it less uncomfortable or creepy. Factors such as past experiences with AI technology could shape perceptions. If applicants have had negative experiences or heard of instances where AI sorting led to unfavorable outcomes, it could contribute to a less positive perception. The resume screening stage is where most candidates are eliminated (Lacroux & Martin-Lacroux, 2022). As well, applicants may have issues with perceptions of bias in AI algorithms, which could affect their comfort levels of the process. Overall, the median results show that all roles were neutral in creepiness. The mean results show applicants as slightly more uncomfortable with AI use in this step of the recruitments process.

Validity (S3.3) measure was analyzed by a Kruskal-Wallis H test was run to determine if there were differences in S3.3 score between three groups of participants with different roles: the "AI expert" (n=19), "applicant" (n=70), and "recruiter" (n=34) role groups. Values are mean ranks unless otherwise stated. Distributions of S3.3 scores were not similar for all groups, as assessed by visual inspection of a boxplot. The mean ranks of S3.3 scores were statistically significantly different between groups, $\chi2(2) = 7.593$, $p = 0.022$. Subsequently, pairwise comparisons were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons. Adjusted p-values are presented. Values are mean ranks unless otherwise stated. This post hoc analysis revealed statistically significant differences in S3.3 sores between the applicant (mean rank=57.74) and recruiter (mean rank=67.65), (p=0.030), but not between the applicant (mean rank=57.74) and AI expert (mean rank= 67.61), (p=0.318), and the AI expert (mean rank= 67.61) and recruiter (mean rank=67.65), (p=1.000). Recruiters' perceptions ranged within neutral to agree in mean with measure of predictive validity S3.3, See table 4.4.

For measure of "Chance to perform" (S3.2) a Kruskal-Wallis H test was run to determine if there were differences in S3.2 score between three groups of participants with different roles: the "AI expert" (n=19), "applicant" (n=70), and "recruiter" (n=34) role groups. Values are mean ranks unless otherwise stated. Distributions of S3.2 scores were not similar for all groups, as assessed by visual inspection of a boxplot. The mean ranks of S3.2 scores were statistically significantly different between groups, $\chi2(2) = 6.574$, $p = 0.037$. Subsequently, pairwise comparisons were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons. Adjusted p-values are presented. Values are mean ranks unless otherwise stated. This post hoc analysis revealed statistically significant differences in S3.2 scores between the applicant (mean rank=58.86) and AI expert (mean rank= 71.82), (p=0.041), but not between applicant (mean rank=58.86) and recruiter (mean rank=62.99), (p=0.547) group and the AI expert (mean rank= 71.82) and recruiter (mean rank=62.99), (p=0.631).

These findings provide insights into role-specific variations. In this case AI experts believe that the use of AI in resume sorting allows candidates the chance to perform and showcase their skills and abilities through their resumes as compared to applicants. It was found that most AI experts feel more comfortable with the use of AI at this step, this may be due to their expertise. This might lead them to believe that AI algorithms can effectively identify and highlight relevant skills and experiences, providing candidates with a fair chance to showcase their abilities.

AI experts may see resume screening with AI as a method of analyzing resume quicker, efficiently reduce human bias and with valid results (Kleinberg et al., 2018). According to our findings, AI experts acknowledge the validity of the outcomes generated through this AI-driven method. Due to their knowledge background, AI experts may discern little discrepancy in the validity of data analysis between human recruiters and AI algorithms when assessing resume information. Consequently, they may believe that the chance for candidates to demonstrate their abilities is not compromised since the evaluation process relies on the data extracted directly from resumes. Since applicants are responsible for building their resumes and can include or exclude experiences and previous roles. This means that the analysis is purely based on the content provided in the resumes and is not influenced by human biases or subjective interpretations.

These varying perceptions can be linked to the depth of knowledge, exposure, and experience each group has concerning AI technology. Applicants might have reservations about its fairness and reliability, while recruiters, familiar with its applications, exhibit a more accepting view. AI experts, due to their expertise, tend to hold a positive outlook on the validity of AI in recruitment, understanding its capabilities and potential benefits. It was pre-measured in D5, discussed in chapter 3.8, which revealed that recruiters and AI experts exhibited higher confidence in general AI capabilities for analyzing data compared to applicants. This observation provides a potential explanation for the similar results observed in S3 regarding AI decision-making in the recruitment process.

Other studies have found that “predictive validity... and opportunity to perform were positively associated with applicants’ fairness perceptions” (Warszta, 2012, p. 62). Meaning negative views on predictive validity and opportunity to perform would result in negative views on fairness perceptions. To analyze the perception of fairness within the roles, we measured mean and median values.

When analyzing the medians for perceived opportunity to perform and validity, we find that AI experts are neutral and agreeing, respectively, whilst finding it fair. Similar is the case with recruiters, where they are neutral to positive with AI’s role and in terms of validity and opportunity to perform but are neutral to its fairness. Applicants disagree with the opportunity to perform, are neutral to AI’s validity and neutral towards its fairness. Overall, there was no significant difference among the role's perception of fairness (p=0.140)

The relationship between validity and fairness aligns with existing literature, as indicated in the study by Langer et al., (2017). However, in applicants' case, the connection between the opportunity to perform and fairness contradicted prior research findings. This discrepancy might arise due to the complete objectivity inherent in the measures used. The survey statement regarding fairness pertained to the overall selection procedure's fairness considering all factors. Participants may have perceived the use of AI as a screening tool differently, particularly in how confident they were about the tool's accuracy in assessing their resumes' depth, reflecting their skills and abilities. Notably, the participants' self-assurance in crafting an impactful resume was not gauged, which could influence their perceptions (Georgiou & Nikolaou, 2020).

Aligning with this a study has found that participants recognize the consistency of algorithmic screening (output accuracy), but still reported lower score for opportunity to perform and predictive validity (Noble et al., 2021). Likewise, applicants showed higher fairness and ability to judge human character for human resume screening compared to algorithmic screening (M. K. Lee, 2018), despite humans spending less than 10 seconds reading each resume ("Ladders Updates Popular Recruiter Eye-Tracking Study with New Key Insights on How Job Seekers Can Improve Their Resumes," 2018). Specifically, applicants perceive it to be unfair that algorithms cannot make exceptions whereas human raters can (M. K. Lee, 2018). Showing that applicants see that there is less opportunity to perform when algorithms are making the decisions since they are unable to be easily manipulated. Therefore, efforts in implementing AI to make recruitment decisions more fair and less biased, resulted in being perceived as less fair (Hilliard et al., 2022), as shown in our thesis. Addressing fairness concerns, an AI expert and an applicant (Participant 17 and 9, respectively) emphasized issues related to the screening process. Participant 17 raised a specific concern about the potential unfairness of the screening process due to its reliance on keywords and high-frequency terms. They noted that unless the screening program is designed to comprehend context, it remains as unjust as traditional ATS. In Participant 17's words,

"At the end of the day, ATS and AI are just gonna base it on keywords and highest frequency terms. Unless the screening program is built to understand context, then it's as unfair as ATS."

Participant 9 echoed similar sentiments, asserting that human recruiters possess a nuanced understanding that algorithms may lack, particularly in striking a balance within resumes. Their perspective highlighted a discomfort with the perceived limitations of AI algorithms in capturing subtle nuances during the initial screening process. Participant 9 expressed,

"The most uncomfortable and unfair part for me when using AI in recruiting felt when I thought that a human decision could have detected some nuances that an AI algorithm could not. Such as the initial screening process, when, for example, a certain skill or experience is lacking, but a certain activity or community work could've showed a more needed aspect of the applicant's skills."

Participant 84, an applicant, expresses a level of trust in AI but concurs with Participant 9's perspective regarding certain limitations in its functionality. Participant 84 states,

"I don't mistrust the use of these AI systems, but I feel like a lot of great employees slip through the cracks because of keywords that aren't being used or arbitrary metrics that don't actually have much to do with job success."

This viewpoint emphasizes the potential drawbacks of AI systems in recruiting, specifically highlighting concerns about the possibility of qualified candidates being overlooked due to limitations in the system's criteria. In contrast, Participant 109, a recruiter, holds a positive outlook on the use of AI in S3, considering it a beneficial tool, particularly when used as a screening tool for potential candidates. They express,

"I think it's a cool idea, using it just as a screening."

It's worth noting that Participant 109's positive perspective on using AI as a screening tool does not represent a unanimous view among all recruiters in our dataset. This diversity of opinions is reflected in the mean score of measure S3.3, which is close to neutral. Additionally, the high standard deviation indicates a considerable range of opinions among recruiters regarding the benefits and drawbacks of AI in the screening process. The varied responses from recruiters suggest that while some see the value in using AI for screening potential candidates, others may have reservations or differing perspectives. This nuanced range of opinions emphasizes the complexity and multifaceted nature of the impact that AI has on the recruitment process, particularly in screening applicants. The high standard deviation underscores the need for further exploration and understanding of the diverse viewpoints within the recruiter community regarding the integration of AI in S3 measures.

This underscores the concern that AI may overlook valuable attributes that human recruiters could discern, especially when assessing the broader context of an applicant's qualifications. Generally, Applicants expressed concern over algorithms' inability to make exceptions, unlike human raters, leading to a perception of reduced opportunity to perform since algorithms lack adaptability (M. K. Lee, 2018). This demonstrates that applicants perceive AI-driven decisions as less flexible and fair due to their rigid nature. Despite the intent to enhance fairness and reduce bias in recruitment, the implementation of AI-led decisions was paradoxically perceived as less fair (Hilliard et al., 2022). Our thesis showed a median neutral result for fairness, inability to easily manipulate algorithmic rater could have affected the results.

In addition, informing participants about the utilization of an AI-driven screening tool for resume analysis might have positively influenced their fairness evaluations. It is plausible that the fairness assessments were linked more to the transparency of the organization's disclosure about using AI rather than evaluating the actual fairness of the AI tool's implementation. This divergence could explain the mixed results observed in the study.

Our research reveals a consistent concern about privacy perceptions among participants, irrespective of their roles (p=0.675). Notably, AI experts exhibited a heightened level of apprehension regarding privacy compared to both applicants and recruiters, with mean ranks of 3.21, 3.16, and 2.97, respectively. A comprehensive overview of all mean values for S3 measures can be found in Table 4.4. One AI expert, participant 82, voiced their unease, stating,

"AI and data privacy measures and standards aren't good enough right now to be so utilized in the hiring process."

This sentiment underscores the notion that, according to at least one AI expert, the existing measures and standards related to AI and data privacy may not be sufficiently robust to support extensive utilization in the hiring process. The higher mean rank (S3.7:3.21) for AI experts indicates a discernible emphasis on the need for more stringent privacy considerations in the integration of AI within hiring practices.

In general, privacy concerns should be worrisome for organizations, because previous research has shown that increased privacy concerns and higher emotional creepiness perceptions lead to lower test-taking motivation and impaired organizational intentions (e.g., recommending the organizations to friends, Bauer et al., (2006) as shown in Langer et al., (2017)). Also, creepiness may cause individuals to refrain from using or participating in interactions with modern technologies, this would have a negative impression of the organization using such technologies (Langer et al., 2017; Polonetsky & Tene, 2015). However, the contrary was found. Despite negative perceptions on privacy and mixed emotional creepiness, organizational perceptions were not negatively affected, and the results were consistent between the three roles (p=0.218). Organizations that use resume screening tools in their recruitment may be comforted that the use of AI at this stage did not negatively affect organizational attractiveness.

Table 4.4: Mean and Standard Deviation (SD) Values of Measures Across AI Experts, Applicants, and Recruiters for Stage S3

	AI Expert		Applicant		Recruiter	
Survey Question	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
S3.1 - Fair	3.47	1.17	2.91	1.10	2.97	1.03
S3.2 -Chance to perform	3.26	1.19	2.50	1.05	2.82	1.19
S3.3 -Validity	3.11	1.29	2.59	1.00	3.15	1.13
S3.4 - Satisfied	3.37	1.16	2.73	1.01	2.82	1.14
S3.5 - Creepy	2.74	1.15	3.29	1.07	2.76	1.21
S3.6 Organization	4.00	0.82	3.56	1.00	3.68	1.01
S3.7 Privacy	3.21	1.23	3.16	1.16	2.97	1.00

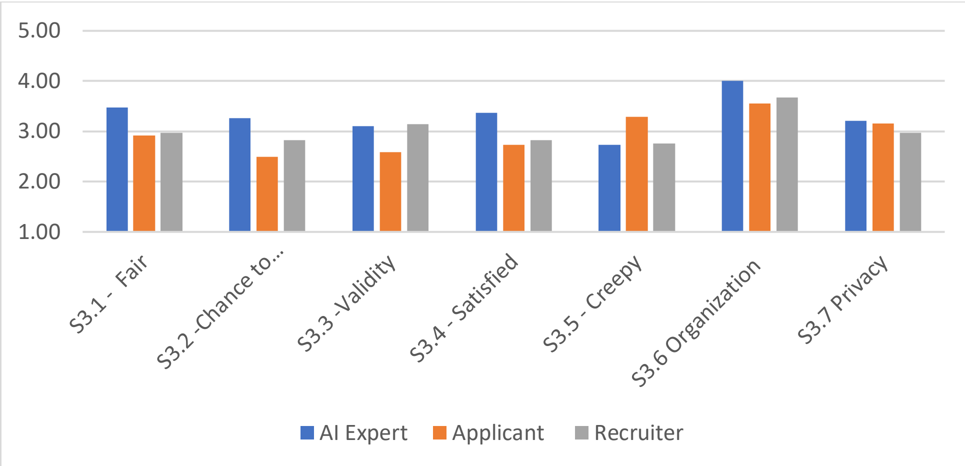

Figure 4.4: Perceptual Insights- Mean Values across S3.1 to S3.7 for AI Experts, Applicants, and Recruiters.

4.5 AI in Gamified Assessments, S4

Gamification refers to the use of gaming elements in non-game settings such as recruitment and selection (Armstrong & Taylor, 2014). In this context it can be used as a personality test or situational judgement test in a gamified manner (Potočnik et al., 2021). In its early research it has been found to be reliable and valid as a selection tool (Georgiou & Nikolaou, 2020). Gamified assessments not only provide the advantage of acquiring immediate insights into applicants but also serve the dual purpose of maintaining applicant engagement and interest (Armstrong & Taylor, 2014). Our research studies whether applicants, recruiters and AI experts perceive this tool to be fair, accurate, creepy, and if it retains organizational attractiveness. Refer to Tables 4.5 and 4.6, and Figures 4.5 and 4.6, for mean perceptual values of S4.

We found no significant differences in any measure of perceptions among the three groups. The observed fairness perceptions (p=0.306), satisfaction (p=0.208), opportunity to perform (p=0.757), privacy (p=0.749), and emotional creepiness (p=0.492) leaned toward neutrality based on mean observations. With regards to validity, we found that the median for AI experts was neutral and closer to disagree for applicants and recruiters, although the ANOVA test suggests there is no significant difference in privacy concern perception among the roles (p=0.508). The organizational perception measure revealed no significant difference among participants (p=0.499), with the majority responding neutrally (scored close to 3). Equal numbers were observed for both strongly disagree and agree, with slightly higher counts for agree. This distribution of responses could potentially be attributed to participants' self-scores on hesitancy towards modern technologies, as indicated in D3 in Chapter 3.8. The results suggest that, in general, most participants do not exhibit hesitancy towards trying out modern technologies. This lack of hesitancy may contribute to their slight positive perception of the organization. Despite having privacy concerns and experiencing emotional creepiness, participants still express a willingness to recommend the organization to others. The standard deviations close to or above 1.00 across all measures indicate that the data results are spread out, reflecting mixed responses among participants in different roles. This variability is further illustrated in Table 4.5, which shows mean ranks and standard deviation values.

The results from our study found no difference in perceptions among the three roles but did find difference in perceptions among those who played video games often and those that do not, which could explain the standard deviation status. The gaming habits were dispersed into three categories, participants who play video games often, a neutral amount, and non-gamers. Those that played video games often and a neutral amount had significantly more positive perceptions of gamified assessments, see Table 4.6. for mean values and standard deviation. Overall, participants were neutral and equally dispersed with their privacy perceptions. There were no significant differences in privacy perceptions based on roles (p=0.275) or based on gaming habits (p=0.612). Nor did they find this use of AI in gamified assessments as a valid assessment tool. No statistical significance was found among roles (p=0.471) or among "gamers" (p=0.094).

Measures S4.2.1 (p=0.002), S4.2.2 (p=0.001), S4.2.4 (p<0.01), S4.2.5(p=0.002), and S4.2.6 (p=0.014), all showed significant differences among gaming habits in ANOVA testing. For Fairness (S4.2.1), Kruskal-Wallis H test was run to determine if there were differences in S4.2.1 score between three groups of participants with different gaming habits: the "gamers_play_often" (n=63), "gamers_play_notoften" (n=42), and "gamers_play_neutral" (n=18) role groups. Values are mean ranks unless otherwise stated. Distributions of S4.2.1 scores were not similar for all groups, as assessed by visual inspection of a boxplot. For fairness perceptions, the mean ranks of S4.2.1 scores were statistically significantly different between groups, the distributions of S4.2.1 scores were statistically significantly different between groups, $\chi2(2) = 12.09$, $p = 0.002$. Subsequently, pairwise comparisons were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons. Adjusted p-values are presented. Values are mean ranks unless otherwise stated. Values are mean ranks unless otherwise stated. This post hoc analysis revealed statistically significant differences in S4.2.1 scores between the gamers_play_often (mean rank= 68.88) and gamers_play_notoften (mean rank= 47.07), (p=0.005), and between gamers_play_notoften (mean rank= 47.07) and gamers_play_neutral (mean rank= 72.75), (p=0.025), but not between the gamers_play_neutral (mean rank= 72.75) and gamers_play_often (mean rank= 68.88), (p=1.00).

For Chance to perform (S4.2.2) the mean ranks of S4.2.2 scores were statistically significantly different between groups, the distributions of S4.2.2 scores were statistically significantly different between groups, $\chi2(2) = 13.043$, $p = 0.001$. Subsequently, pairwise comparisons were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons. Adjusted p-values are presented. Values are mean ranks unless otherwise stated. Values are mean ranks unless otherwise stated. This post hoc analysis revealed statistically significant differences in S4.2.2 scores between the gamers_play_often (mean rank= 70.33) and gamers_play_notoften (mean rank= 46.51), (p=0.001), but not between the gamers_play_neutral (mean rank= 69.00) or any other group.

For Satisfied (S4.2.4), the mean ranks of S4.2.4 scores were statistically significantly different between groups, the distributions of S4.2.4 scores were statistically significantly different between groups, $\chi2(2) = 14.37$, $p <0.001$. Subsequently, pairwise comparisons were performed using

Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons. Adjusted p-values are presented. Values are mean ranks unless otherwise stated. Values are mean ranks unless otherwise stated. This post hoc analysis revealed statistically significant differences in S4.2.4 scores between the gamers_play_often (mean rank= 70.51) and gamers_play_notoften (mean rank= 45.64), (p=0.001), and between gamers_play_notoften (mean rank= 45.64) and gamers_play_neutral (mean rank= 70.39), (p=0.032), but not between the gamers_play_neutral (mean rank= 70.39) and gamers_play_often (mean rank= 70.51), (p=1.00).

For Creepiness (S4.2.5), the mean ranks of S4.2.5 scores were statistically significantly different between groups, the distributions of S4.2.5 scores were statistically significantly different between groups, $\chi2(2) = 12.843$, $p = 0.002$. Subsequently, pairwise comparisons were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons. Adjusted p-values are presented. Values are mean ranks unless otherwise stated. Values are mean ranks unless otherwise stated. This post hoc analysis revealed statistically significant differences in S4.2.5 scores between the gamers_play_often (mean rank= 52.41) and gamers_play_notoften (mean rank= 77.04), (p=0.001), but not between the gamers_play_neutral (mean rank= 60.47) or any other group.

For Organization perceptions (S4.2.6), the mean ranks of S4.2.6 scores were statistically significantly different between groups, the distributions of S4.2.6 scores were statistically significantly different between groups, $\chi2(2) = 8.569$, $p = 0.014$. Subsequently, pairwise comparisons were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons. Adjusted p-values are presented. Values are mean ranks unless otherwise stated. Values are mean ranks unless otherwise stated. This post hoc analysis revealed statistically significant differences in S4.2.6 scores between the gamers_play_often (mean rank= 68.01) and gamers_play_notoften (mean rank= 49.61), (p=0.019), but not between the gamers_play_neutral (mean rank= 69.89) or any other group.

For the discussion we will primarily concentrate on two groups of participants: those who reported playing video games often and those who do not. We have chosen to exclude individuals who play a neutral amount, due to the subjective nature of self-assessment, as participants' perceptions of what constitutes "often" may vary. This decision aims to mitigate potential inconsistencies in categorization. It is noteworthy that no significant differences were observed among AI experts, applicants, and recruiters in terms of their roles. Consequently, we anticipate that exploring gaming habits will yield valuable insights into perceptions of gamified assessments.

Based on the mean ranks neutral gamers (gamers_play_neutral) have no significant difference with the other two groups. In measures of perceptions of opportunity to perform, fairness, creepiness, and organizational attraction we see a clear positive perception and a statistically significant difference among the participants who play video games often (gamers_play_often) than those who do not (gamers_play_notoften).

Compared to traditional situational judgement tests, game-based situational judgement tests are viewed as fairer and have increased organizational attractiveness (Georgiou & Nikolaou, 2020). Some benefits include shorter testing times (Hilliard et al., 2022; Wright & Atkinson, n.d.), more satisfying (Georgiou & Nikolaou, 2020), more immersive (Hilliard et al., 2022), and are perceived as more engaging (Lieberoth, 2015), than their questionnaire-based equivalents. In contrast, gamified assessment could also “garner skepticism from candidates who cannot conceive the connection between playing games and performing job tasks” (Ellison et al., 2020, p. 243). Specifically, those with less video gaming experience may feel at a disadvantage to showcase their skills (Bauer et al., 2011). Likewise, unfamiliarity could cause lower perceived validity associated with gamified assessments (Ellison et al., 2020). Aligning with previous research, our findings indicate that participants who play video games often find AI-gamified assessments as fairer, more satisfying, have higher perceived opportunity to perform, increased organizational attractiveness and lower creepiness perceptions than those who do not play video games. However, an intriguing perspective emerges from Participant 9, an applicant who does not play video games. Despite not being a regular gamer, they express a positive outlook on gamified assessments as long as they extract pertinent and qualified skills. Participant 9 emphasizes,

"Gamified assessments, I like the idea a lot, but only if the assessments would indeed reflect the required skills."

This viewpoint underscores the potential efficacy of gamified assessments, provided they accurately capture the relevant skills sought in the recruitment process. Participant 117, who is a recruiter and plays video games regularly, holds a contrasting viewpoint. They express concerns about the fairness of gamified assessments, asserting that individuals who are seasoned gamers might gain an undue advantage over those who are not familiar with gaming dynamics. Participant 117 states,

"I also feel like turning recruitment into a game-like experience would give experienced gamers a huge and unfair advantage."

This perspective raises considerations about the potential bias introduced by gamified assessments, particularly when individuals with gaming expertise may navigate them more adeptly, potentially skewing the evaluation process in favor of experienced gamers.

Table 4.5: Mean and Standard Deviation (SD) Values of Measures Across AI Experts, Applicants, and Recruiters for Stage S4

	AI Expert		**Applicant**		**Recruiter**	
Survey Question	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
S4.1 - Fair	3.11	1.10	3.00	1.14	2.91	1.22
S4.2 -Chance to perform	3.26	1.15	3.09	1.03	3.03	1.24
S4.3 -Validity	2.68	0.95	2.34	1.08	2.41	1.13
S4.4 - Satisfied	3.26	1.19	2.94	1.09	2.79	1.17
S4.5 - Creepy	2.95	1.13	3.04	1.07	2.79	1.32
S4.6 Organization	3.26	0.99	3.04	0.91	2.91	1.29
S4.7 Privacy	2.74	0.99	3.11	1.23	2.82	0.87

Table 4.6: Mean, Median, and standard deviation values of measures based on gaming habits.

Measure	Gamers_play_not often			Gamers_play_neutral			Gamers_play_often		
	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
S4.2.1-fair	2.50	1.110	2.50	3.33	0.767	3.50	3.22	1.170	3.00
S4.2.2-Chance to perform	2.62	0.987	3.00	3.33	0.767	3.50	3.35	1.166	4.00
S4.2.3-Validity	2.19	0.943	2.00	2.22	0.647	2.00	2.62	1.211	3.00
S4.2.4-Satisfied	2.43	1.039	2.00	3.28	0.895	3.00	3.21	1.138	3.00
S4.2.5-Creepy	3.48	1.087	4.00	2.89	0.676	3.00	2.63	1.182	3.00
S4.2.6-Organization	2.67	0.979	3.00	3.28	0.461	3.00	3.22	1.128	3.00
S4.2.7 Privacy	3.02	1.115	3.00	3.17	0.985	3.00	2.89	1.152	3.00

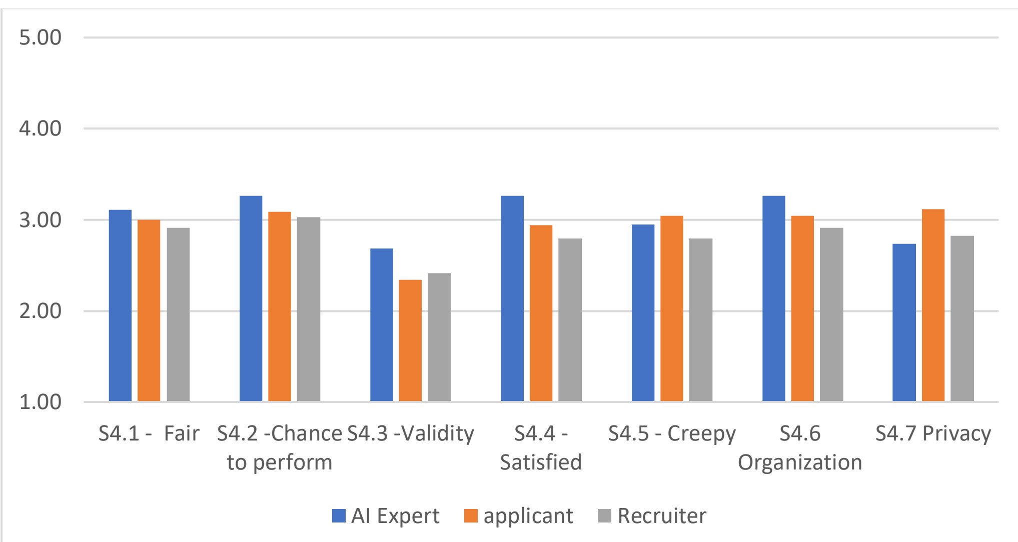

Figure 4.5: Perceptual Insights- Mean Values across S4.1 to S4.7 for AI Experts, Applicants, and Recruiters.

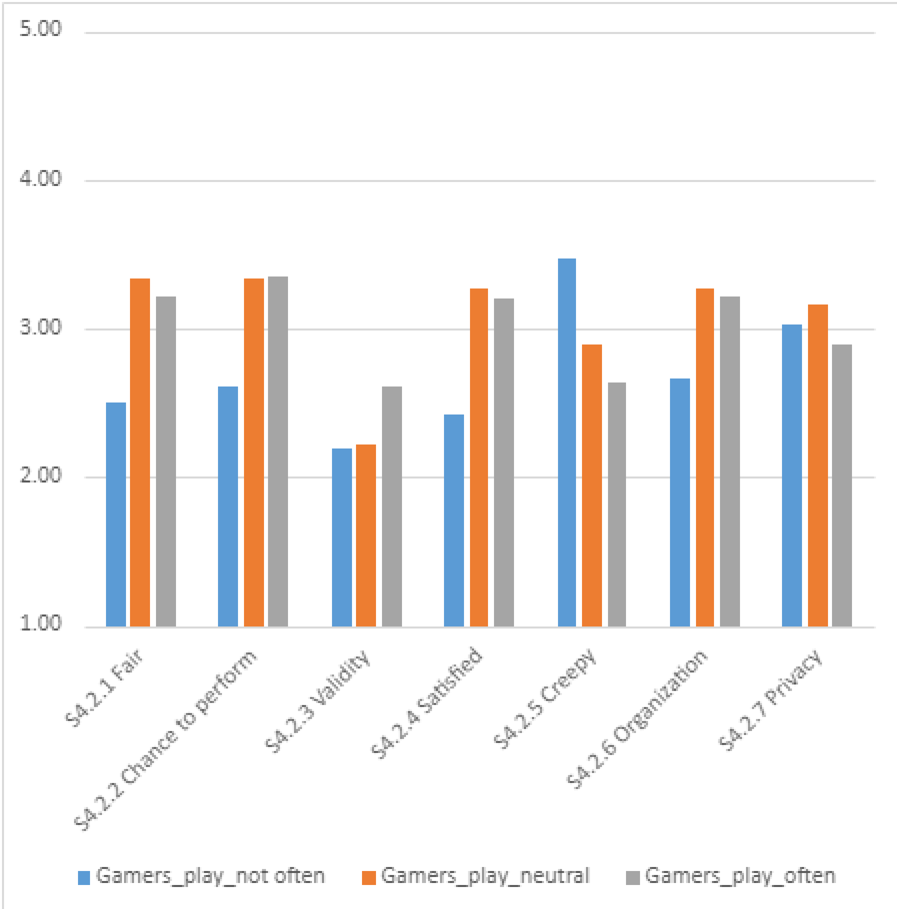

Figure 4.6: Perceptual Insights- Mean Values across S4.1 to S4.7 based on gaming habits; often, neutral, and not often.

4.6 Digital AI Interviews, S5

Digital or AI-based interviews involve candidates recording their responses to a standardized set of questions, which are then assessed by AI-powered computer systems (Guchait et al., 2014). The employment interview stands as a pivotal component in the employee selection process (Nikolaou & Georgiou, 2018). Therefore, it is imperative for researchers in personnel psychology and human resource practitioners to comprehend the perceptions of this process. There is a unique nature of each interview, as none is like the other, but research has shown that aspects of the interview including interviewer traits can influence candidates' perceptions of the interview (Nikolaou, 2011). Refer to Table 4.7 and Figure 4.7 for mean perceptual values of S5 and Table 7.9 in Appendix B for the ANOVA results.

Participants' survey response highlighted a sense of threat and generated sense of creepiness (p=0.492) during AI-based interviews, potentially stemming from the uncommon nature of these interviews compared to more conventional video-conferencing setups in e-recruitment. These unconventional interview formats can elicit adverse responses due to their novelty, potentially reducing as digital interviews become more prevalent in the future (Chamorro-Premuzic et al., 2016).

The perception of creepiness might also be associated with the avatar's appearance. Participants were not provided with a specific description of the avatar, allowing for subjective interpretations. Avatars that closely resemble humans might trigger feelings of unease; a phenomenon known as the uncanny valley effect. Additionally, research suggests that interview ratings can be influenced by the attractiveness of avatars, where more appealing avatars garner more positive ratings (Behrend et al., 2012). High levels of discomfort or negative views regarding AI-based interviews could adversely impact organizations. Such reactions might prompt applicants to cancel interviews or form unfavorable opinions about the organization (Van Hoye et al., 2009). Moreover, concerns over privacy regarding shared data during the interview process could exacerbate these perceptions. Studies indicate that increased privacy concerns tend to correlate with diminished organizational intentions (Langer et al., 2017; McCarthy et al., 2017)

Interestingly, despite the participants’ expressed apprehension about privacy concern ($p=0.749$) and creepiness perceptions ($p=0.492$), most indicated a willingness to proceed with the AI avatar interview if invited by the company ($p=0.297$). This observation suggests that, contrary to initial assumptions, these concerns might not significantly influence applicants' decisions. Resulting in creepiness and privacy as not being a detrimental factor affecting organizational views. This information may be comforting to organizations who currently or plan to use AI-interviews, aligning with previous research in comparison of digital interviews and videoconference interviews (Langer et al., 2017). Such findings could offer reassurance to organizations employing AI-based interviews, indicating that the anticipated negative impacts of creepiness perceptions and privacy concerns might not significantly affect organizational perceptions. Despite initial concerns, participants seem inclined to proceed with AI avatar interviews if invited by the company. This suggests that the identified worries may not significantly deter applicants, providing insights that could alleviate some organizational apprehensions regarding potential negative effects related to privacy concerns and perceptions of creepiness associated with AI-based interview processes. This finding contrasts with prior research that suggested such factors could detrimentally influence an organization's reputation (Langer et al., 2017).

The information about participants' experimentation propensity, as outlined in D1 and detailed in Section 3.8, reveals a noteworthy observation. Participants across various roles scored themselves with high experimentation propensity. This data, available in Table 7.3 in Appendix A, is significant as it sheds light on a potential explanation for the lack of negative effects on organizational perceptions caused by creepiness and privacy concerns. The high scores in experimentation propensity indicate that participants in the study possess a strong inclination and curiosity to experiment with modern technologies. This characteristic may influence their perceptions of AI in the recruitment process. The participants' openness to experimentation could contribute to a more positive reception of AI technologies, possibly mitigating the negative impact that factors like creepiness and privacy concerns might have on organizational perceptions. This adds a valuable dimension to understanding how participants' personal traits, such as experimentation propensity, may shape their attitudes toward AI adoption in organizational contexts. However, it is essential to note that although the mean values of organizational perception were moderately high, some applicants expressed concerns about AI's limitations in processing soft skills and emphasized the importance of human recruiters being involved in S5. Participant 72, an applicant, highlighted their perspective, stating,

"AI should not make decisions unassisted, nor should social cues like vocal or facial features be used. AI offers great benefits, but risks reinforcing standing biases and discrimination, especially if most employees at a company are from privileged groups."

This viewpoint underscores the potential risks associated with relying solely on AI in the recruitment process, emphasizing the need for human involvement to mitigate biases and discrimination, particularly in assessing soft skills and nuanced social cues. Organizations should consider these perspectives and carefully balance the benefits of AI with the importance of human oversight in recruitment processes.

Regarding fairness perceptions, applicant mean values showed that they did not find AI-interviews fair, and recruiters and AI experts leaned closer to neutral see table 4.6.1. Although the differences among roles were not statistically significant (p=0.306), we can interpret that the applicants may find AI-interviews as less fair due to its overall lack of humanization of the interview process (Nørskov et al., 2020). A negative factor that may have impact on fairness perceptions may be due to the information provided in the scenario, specifically the applicant features that are analyzed during the interview process like non-verbal cues (Langer et al., 2021; Newman et al., 2020). Applicants perceive a selection situation as fair if their justice expectations are met (Gilliland, 1993). Additionally, an applicant highlighted another crucial factor influencing fairness perceptions, emphasizing the impact of the absence of a human recruiter on the candidate's perspective of the organization. Participant 9 articulated,

"I don't find it fair to be interviewed by a chatbot or an avatar, as the interview is a chance for companies to interview applicants. It's also a chance for the applicant to interview the employer; he or she wants to see the employer, talk to them, and decide if they would like to work for them. Therefore, it isn't fair to make it a one-way interview in that sense."

This participant's viewpoint underscores the reciprocal nature of the interview process, where both the employer and the applicant assess each other. The absence of a human recruiter in the interview process is perceived as limiting the candidate's ability to evaluate the organization and make an informed decision about whether they want to work for them. This insight highlights the importance of considering the mutual evaluation aspect in the recruitment process to enhance fairness perceptions from the applicant's perspective. Our findings show that participants had negative to neutral fairness perceptions for digital interviews that use AI raters, see Table 4.7 for mean values. Findings from Suen et al., (2019) found no difference in fairness perception in digital interviews that use AI or human raters. Other studies have found that compared to robot-mediated interviews, participants preferred face-to-face interviews (Nørskov et al., 2020). These findings can discern that while digital interviews using AI may not elicit strong fairness or unfairness perceptions, the preference for face-to-face interviews persists among applicants. This data hints at the ongoing relevance of traditional interview formats despite advancements in digital interview technologies. In addition, studies found that applicants perceived digital interviews as "creepier, induced privacy concern, and lower fairness perceptions" compared to video-conference interviews (Langer et al., 2017, p. 376).

This study's findings reveal no significant differences among the roles in terms of for perceived fairness (p=0.306), validity (p=0.508), privacy (p=0.749), and satisfaction (p=0.208). However, participants express discomfort with the absence of human raters and recruiters in the interview process. Several participants underscore the importance of human involvement in the interview process, emphasizing that the lack of human interaction in S5 deviates from real-world experiences. Participant 67, an applicant, voices a preference for human-conducted interviews, stating,

"I would still prefer a human to conduct my interviews because algorithm is not all that in the world. If I am selected and going to be working with the team, an interview is a great opportunity for them to assess me. I feel AI would be too straightforward and has lack of real-world thinking."

Concerns about the impersonal nature of AI in recruitment are echoed by Participant 83, an applicant, who finds the idea.

"Disturbingly impersonal and alienating."

They express wariness due to AI's lack of human thoughts and feelings. These sentiments align with the moderately high perceptions of creepiness (S5.5) in S5.5, particularly noted by applicants, see Table 4.7.

Low scores on chance to perform (S5.2), especially among applicants and recruiters, may be attributed to the absence of options to choose a human recruiter for the interview. Participant 98, an applicant, advocates for candidates to have the option to choose a human interviewer, stating,

"There should always be an option to have a real human step in and get involved as an alternative."

Another applicant, Participant 86, emphasizes the need for a balance between AI and basic human interaction.

"There needs to be a balance between AI and basic human interaction."

These viewpoints highlight the importance of providing flexibility and choices, particularly acknowledging individual preferences and potential challenges, such as those related to technology or disabilities, see chapter 2.6.1. Participant 74, a recruiter, suggests collaboration between AI and human recruiters, noting that not everyone is adept with technology.

"Not everybody is good with technology so there should always be a second option to speak to a human being when required for assistance."

With regards to "Chance to perform" (S5.2), A Kruskal-Wallis H test was run to determine if there were differences in S5.2 score between three groups of participants with different roles: the "AI expert" (n=19), "applicant" (n=70), and "recruiter" (n=34) role groups. Values are mean ranks unless otherwise stated. Distributions of S5.2 scores were not similar for all groups, as assessed by visual inspection of a boxplot. The mean ranks of S5.2 scores were statistically significantly different between groups, the distributions of S5.2 scores were statistically significantly different between groups, $\chi2(2) = 6.823$, $p = 0.033$. Subsequently, pairwise comparisons were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons. Adjusted p-values are presented. Values are mean ranks unless otherwise stated. Values are mean ranks unless otherwise stated. This post hoc analysis revealed statistically significant differences in S5.2 scores between the applicant (mean rank=56.61)) and AI expert (mean rank=79.82), (p=0.028), but not between the applicant (mean rank=56.61) and recruiter (mean rank=63.34), (p=1.00), and the AI expert (mean rank=79.82) and recruiter (mean rank=63.34), (p=0.291).

The disparity between AI experts' and applicants' perceptions regarding the ability to showcase skills in AI-based interviews is evident from the median scores. AI experts generally agreed that candidates could effectively display their abilities in AI-interviews, while applicants tended to disagree. This discrepancy might arise from distinct levels of familiarity with AI technology and its capacities. AI experts, being more conversant with the technology, likely harbor a more optimistic view of candidates' potential to demonstrate skills in AI-based settings. In contrast, applicants may lack such familiarity, affecting their confidence in presenting their skills effectively within this format.

Research highlights that digital interviews, particularly AI-based ones, might hinder the opportunity for candidates to make a strong "impression" or showcase their full potential compared to face-to-face interactions (Blacksmith et al., 2016). This limitation could impact how applicants perceive their ability to exhibit skills during these interviews. In traditional or e-recruitment interviews, whether face-to-face or online, applicants wield the ability to guide conversations and steer interactions, leveraging their interpersonal skills (Kempf-Leonard, 2005). However, in AI-based interviews, such control is restricted or absent, potentially affecting how applicants perceive their chance to perform optimally. This disparity could arise due to applicants' inclination towards showcasing skills through active people engagement, a facet less feasible in AI-based interviews, thus impacting their perceptions. This aligns with findings that algorithmic assessments are more objective and susceptible to manipulation and therefore participants feel less confident in their ability to influence algorithmic assessments compared to human assessments (Hilliard et al., 2022; Nikolaou, 2011).

The higher mean validity ratings among AI experts regarding AI interviews suggest that they believe in the accuracy of these interviews in assessing applicants' capabilities. Consequently, they're more likely to agree that candidates can indeed display their abilities through such interviews. Applicants may disagree due to limited understanding of the AI system's data analysis or due to perceived discomfort and creepiness levels during the interview process. Factors like nervousness, discomfort, and skepticism about its validity may contribute to their perception of unfairness and their belief that they cannot perform well in this setting. As mentioned, the difference in AI expert and applicant perceptions could stem from factors like familiarity with technology, perceived limitations of digital interviews, and the impact of these formats on candidates' ability to showcase their skills effectively. Applicants and recruiters expressed their concern for the use of AI in digital interviews, specifically in the lack of human interaction. Although a study conducted by Swapna & Arpana (2021) showed that recruiters express a preference for the integration of AI into the interview stage, owing to its favorable impact on decision-making efficiency and cost reduction.

Table 4.7: Mean and Standard Deviation (SD) Values of Measures Across AI Experts, Applicants, and Recruiters for Stage S5

Survey Question	AI Expert		Applicant		Recruiter	
	Mean	SD	Mean	SD	Mean	SD
S5.1 - Fair	3.11	1.29	2.63	1.23	2.82	1.19
S5.2 -Chance to perform	3.37	1.26	2.57	1.11	2.82	1.29
S5.3 -Validity	3.00	1.15	2.66	1.14	2.65	1.30
S5.4 - Satisfied	3.05	1.27	2.49	1.28	2.68	1.15
S5.5 - Creepy	3.05	1.31	3.27	1.30	2.97	1.19
S5.6 Organization	3.47	1.22	3.01	1.20	3.26	1.31
S5.7 Privacy	3.11	1.37	3.27	1.32	3.09	1.14

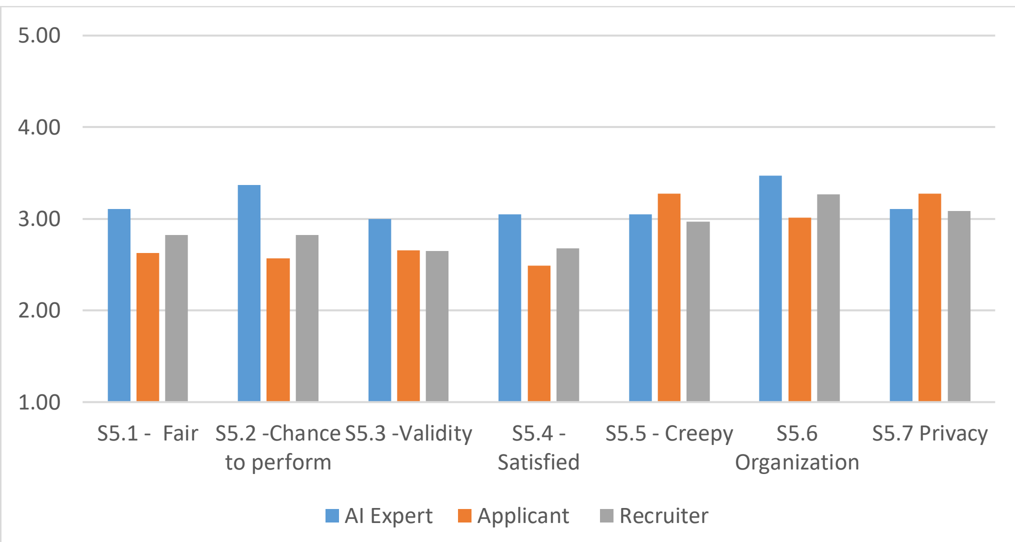

Figure 4.7: Perceptual Insights- Mean Values across S5.1 to S5.7 for AI Experts, Applicants, and Recruiters.

4.7 AI in Final Selection, S6

AI can help organizations or recruiters make decisions faster and smoother (Upadhyay & Khandelwal, 2018). Machine learning programs are using existing data to make decisions, as mentioned before this could cause discrimination and biases, see chapter 2. The existing body of research indicates that reactions to AI-based automated decision-making in personnel selection tend to be predominantly negative (Acikgoz et al., 2020; Gonzalez et al., 2022; Langer et al., 2019;

M. K. Lee, 2018). In this study, D4 specifically measured participants' confidence in AI decision-making, revealing that AI experts held a higher perception of confidence in D4 compared to applicants and recruiters. Refer to Table 4.8 and Figure 4.8 for mean perceptual values of S6 and Table 7.10 in Appendix B for ANOVA results.

This observation was intended to see its likeness with the findings from S6.2, where perceptions of validity were assessed. While there was a significant difference in D4 for general AI decision-making (p=0.0368), S6.2 demonstrated that there was no significant difference among roles concerning perceptions of validity in AI decision-making within the recruitment process (p=0.395). This suggests that although there is a divergence in confidence perceptions among participant roles, particularly in the general context of AI decision-making, this discrepancy does not extend to perceptions of validity in the specific domain of AI decision-making within the recruitment process.

Our study found the medians for all three roles with respect to measures of fairness, satisfaction, and creepiness was 3-neutral, See Table 4.8 for mean values. An equal number of respondents believed that AI in selection was fair, unfair, and neutral. All three groups median expressed feelings of neutrality towards fairness of AI use in selection stage. We found no statistically significant difference for any of roles' perception measurements of fairness (p=0.558), satisfaction (p=0.936), emotional creepiness (p=0.464), organizational attractiveness (p=0.866), and privacy (p=0.053) but this was close to the significance threshold of 0.05.

Perhaps participants were inclined to have higher perceived fairness reactions due to the reasoning in the scenario provided to the participants that the AI system is basing its selection on previous "data" obtained from the gamified assessment, AI-interviews, and resume screening. Participants who did not find those methods fair did not find selection based on those methods as fair either. Participants equally may have felt that this is why the results are unfair, because they may not understand how the data is analyzed through the algorithm. Transparency on the algorithms decision making process is important, and if not properly understood it leads to negative perception (Gilliland, 1993; Woods et al., 2020). Several participants, particularly those in applicant roles, shared apprehensions about AI decision-making. Participant 72, for instance, strongly believes that AI should not autonomously make decisions without human intervention. They articulate,

"AI should not make decisions unassisted... AI offers great benefits, but risks reinforcing standing biases and discrimination, especially if most employees at a company are from privileged groups."

This perspective emphasizes the potential dangers of AI decision-making without human oversight, raising concerns about the perpetuation of existing biases and discrimination, particularly in environments dominated by privileged groups. Participant 65 conveyed ethical concerns related to biased data, disagreeing with AI decision-making on ethical grounds. They assert,

"I disagree with it, ethically. AI is just as biased as those who programmed it."

This viewpoint underscores the ethical implications of relying on AI decision-making processes that may inherently carry biases present in the data and programming. Participant 68 reinforces the previous concerns, emphasizing both ethical considerations and the need for human assistance in decision-making by AI. They share a sense of wariness, stating,

"I feel wary of it because it does not possess the thoughts and feelings of a human being and is prone to the bias of whoever programmed it."

This perspective underscores the multifaceted concerns surrounding AI decision-making, encompassing ethical dimensions and the potential impact of human biases embedded in the programming of AI systems. Participant 99 articulates a significant concern regarding the absence of human interaction in the decision-making process of recruitment. They express apprehension about the impersonal nature of AI, emphasizing that it deprives candidates of the opportunity to actively demonstrate and showcase their abilities. This sentiment aligns with earlier concerns raised in S3, S4, and S5. In Participant 99's words,

"There really is no replacing actual human contact between a possible employer and a potential candidate. I don't want a machine deciding whether I am a good fit or, ultimately, whether I get to pay my bills or not, without speaking with a real person at some point in the process."

This perspective underscores the deep-seated belief in the irreplaceable value of human interaction in the recruitment process, particularly in assessing the fit between an individual and a potential employer. The participant further emphasizes the limitations of AI, stating,

"A person cannot display who they really are or what they bring to the table while being 100% judged by a machine or algorithm. It feels VERY foreign and clinical to me - no warmth or rapport at all."

This sentiment highlights the perceived lack of S6.1, S6.2, S6.3, and S6.7. Previous research indicates that AI-driven hiring decisions are perceived as less fair compared to those made by humans (M. K. Lee, 2018). Two theories, fairness heuristic and signaling theory, offer valuable insight into understanding applicants' reactions to AI usage in the hiring process. Fairness heuristic theory explains how individuals create a 'fairness heuristic' guiding their expectations and reducing uncertainty in ambiguous situations (McCarthy et al., 2017). Candidates often depend on their cognitive shortcuts or rules of thumb, known as fairness heuristics. These heuristics help candidates interpret and make sense of the organization's actions, processes, and results during the interview, particularly when they have limited knowledge about how the organization operates (McCarthy et al., 2017). When AI becomes the decision-maker in interviews, the situation becomes even more uncertain for the interviewees due to the novelty of this approach. As a result, candidates might quickly form these fairness heuristics to judge whether the interview process is fair or not. This rapid judgment based on limited information about AI's role may lead to negative perceptions of justice during the selection process (Acikgoz et al., 2020). Essentially, the unfamiliarity with AI's decision-making process could influence applicants to perceive the process as less fair. Perceptions of fairness, and privacy concerns can be affected by little information regarding how algorithms make decisions and compute judgments (Langer et al., 2018, 2021).

On the other hand, signaling theory proposes that applicants, in the absence of clear organizational transparency, tend to derive conclusions from available information (Mirowska & Mesnet, 2021).

As organizations often lack transparency about their AI utilization, including the algorithms used in scoring, applicants might interpret the absence of human interaction in AI-driven selection as a reflection of the entire organization (Acikgoz et al., 2020). Although the results were close to neutral towards fairness, S6.1, we found this did not negatively affect organization attractiveness, participants would still accept a job from this company even with its use of AI in its selection procedure.

Table 4.8: Mean and Standard Deviation (SD) Values of Measures Across AI Experts, Applicants, and Recruiters for Stage S6

Survey Question	AI Expert		Applicant		Recruiter	
	Mean	SD	Mean	SD	Mean	SD
S6.1 - Fair	3.16	1.17	2.84	1.15	2.97	1.17
S6.2 -Validity	3.16	1.21	2.77	1.05	2.88	1.12
S6.3 -Satisfied	2.95	1.18	2.84	1.07	2.88	1.23
S6.4 - Creepy	3.32	1.11	3.09	1.13	2.91	1.19
S6.5 - Organization	3.47	1.17	3.41	1.06	3.32	0.94
S6.6 Privacy	3.11	1.15	3.77	1.05	3.53	1.05

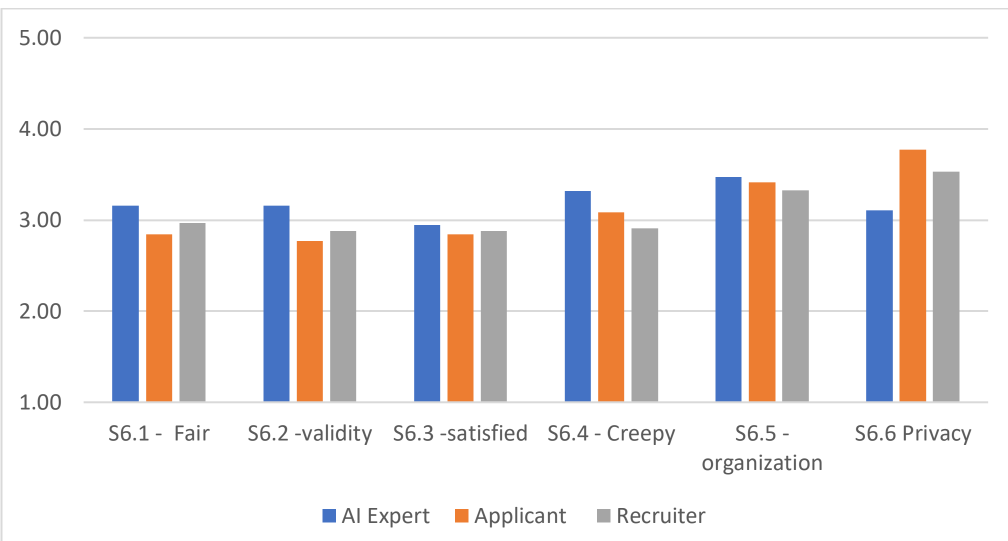

Figure 4.8: Perceptual Insights- Mean Values across S6.1 to S6.7 for AI Experts, Applicants, and Recruiters.

4.8 AI in Communication, S7 and S8

The implementation of AI communication involves the utilization of Chatbots in two distinct steps, both aimed at enhancing communication efficiency within the recruitment process. In the first scenario, denoted as S7, a Chatbot is employed for communication during the recruitment process. Specifically, it is tasked with conveying interview and assessment scores and providing explanations for candidate selection outcomes. This application of Chatbots demonstrates their role in streamlining communication. In the second scenario, referred to as S8, an AI Chatbot is employed as a comprehensive communication tool throughout the recruitment process. In this capacity, Chatbot serves as a versatile assistant, effectively replacing a human recruiter. It takes on a range of responsibilities, including answering questions about the role, outlining requirements, discussing salary details, and engaging in two-way dialogues with candidates. This broader application showcases the adaptability and functionality of AI Chatbots as they take on various communication tasks to facilitate a seamless interaction between candidates and the recruitment process (Upadhyay & Khandelwal, 2018). Tables 4.9 and 4.10 present the mean and standard deviation datasets for S7 and S8. Please refer to Figures 4.9 and 4.10 for the visual representation of mean perceptual values corresponding to S7 and S8, respectively. Additionally, detailed ANOVA results are available in Tables 7.11 and 7.12 of Appendix B.

The level of emotional unease or discomfort—referred to as "emotional creepiness"—was marginally higher when receiving communication regarding selection outcomes (S7.4, p=0.089) compared to the overall communication experienced throughout the recruitment process (S8, p=0.394). This distinction might be understood through the CASA paradigm, which suggests that individuals tend to apply social norms and expectations to computers despite being aware that these machines lack feelings, intentions, or human motivations. Applicants, in particular, might not separate feedback and negative selection outcomes from the chatbot responsible for conveying this information. It's important to note that the chatbot merely transmits the results of the assessment process and doesn't independently make decisions in S7. The lack of human interaction or personal touch in the communication of outcome could also affect these results. Human beings often seek empathetic and nuanced responses that acknowledge their emotions, especially in sensitive situations like feedback on job applications or selection outcomes. The absence of human-like empathy or understanding in communication from Chatbots could contribute to the perceived emotional discomfort.

Despite this, participants still felt comfortable in two-way communication with the chatbot by asking and responding to questions, with no significant difference among the roles (S7.3, p=0.062 and S8.3, p=0.415). This could also be explained by the participants response for D7, which emphasizes their preference in using AI in routine transactions. In essence, the participants' comfort in engaging with the chatbot for questions doesn't directly negate the possibility of experiencing emotional discomfort when receiving specific types of information, particularly outcomes like rejections or negative feedback. The emotional response might be more associated with the content of the communication rather than the act of engaging in conversation with the AI.

The contrary could be said for privacy. A Kruskal-Wallis H test was run to determine if there were differences in Privacy (S7.6) score between three groups of participants with different roles: the "AI expert" (n=19), "applicant" (n=70), and "recruiter" (n=34) role groups. Specifically, for privacy with AI use in communicating selection procedures (S7.6). Values are mean ranks unless otherwise stated. Distributions of S7.6 scores were not similar for all groups, as assessed by visual inspection of a boxplot. The mean ranks of S7.6 scores were statistically significantly different between groups, the distributions of S7.6 scores were statistically significantly different between groups, $\chi2(2) = 8.536$, $p = 0.014$. Subsequently, pairwise comparisons were performed using

Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons. Adjusted p-values are presented. Values are mean ranks unless otherwise stated. Values are mean ranks unless otherwise stated. This post hoc analysis revealed statistically significant differences in S7.6 scores between the applicant (mean rank= 69.41) and AI expert (mean rank=46.71), (p=0.029), but not between the applicant (mean rank= 69.41) and recruiter (mean rank= 55.28), (p=0.139), and the AI expert (mean rank=46.71) and recruiter (mean rank= 55.28), (p=1.00). This showed that AI experts are less concerned about privacy issues than applicants.

However, less concern was found with all participants with regards to AI communication in S8 (p=0.800). AI experts might be less concerned about privacy in the use of chatbots for conveying selection outcomes because of their familiarity and expertise with AI technologies. Their expertise could lead them to trust the system's functionality and security measures more than applicants who might have less understanding or control over the underlying technology. AI experts might perceive chatbots as tools for conveying information without directly accessing sensitive or personal data. When chatbots are utilized throughout the recruitment process rather than specifically for conveying selection outcomes, all participants have reduced privacy concerns. This perception could stem from several factors such as context of Information, control of the information, and data handling perceptions. Selection outcomes often carry sensitive and personally impactful details, potentially triggering higher privacy concerns compared to other routine communications. Throughout the process, the chatbots might predominantly handle general or non-sensitive information, leading participants to feel that their privacy is less compromised. Participants might perceive that when the chatbots are involved in broader communication, the nature and depth of data access might be limited, contributing to lower privacy concerns. As well, participants may be used to using chatbots for routine transactions in other industries. Chatbots are a common tool used on many company websites.

Organizational attractiveness remained the same when Chatbots were responsible for conveying selection outcomes participants (S7, p=0.708), and their use throughout the recruitment process (S8, p=0.719), the overall view was 3-neutral. Participants did not find the organization as more attractive or less when applying AI to communicate selection test scores and outcomes. However, AI experts had a slightly more positive organizational view with the use of Chatbots as communicative tool throughout the recruitment process (S8) as compared to its use for selection results (S7). This increase in positive view towards AI's use in communication throughout the whole process as compared to just in selection communication can be due to expert's understanding of how AI software can benefit the recruitment process. Since AI software can carry out communication with several applicants at once whereas a human recruiter only can do a limited amount in order to keep track of everything (Johansson et al., 2019). Organizational attractiveness may be affected by the lack of "human touch" in communication with the organization. For instance, candidates do not need an opportunity to determine if they like and want to spend more time with chatbots, but moreso they need an opportunity to see if they like to chat and work with real people in the organization. candidates want and need a chance to determine if they like the company culture in which they will be working and the people with whom they will be working (black, 2020). Chatbots take this opportunity away as they may receive response on company culture attributes but may not directly experience them through communicative tools. Human intervention in the process remains important. A study has suggested that the human touch in the recruitment and selection process always remains essential since it is about humans (Dijkkamp, 2019).

Based on median values, a higher percentage of recruiters were more satisfied with Chatbots use and found it more accurate in communicating selection decisions, as compared to applicants and recruiters, although no significant difference (S7, p=0.200 and S8, p=0.837). This may be because they see it as beneficial and time saving for them with mundane tasks such as explaining candidates' outcomes and communicating salary and role descriptions. This may be because they do it so often for so many people with the same information, this tool could benefit them by not repeating themselves and help them focus on other tasks. Especially when considering negative results (candidates who did not get job), the recruiters could focus their attention on positive results (candidates who did get job offer).

There was no significant difference among role in perceptions of validity with either use of chatbot in communication (S7, p=0.813 and S8, p=.878). The perceived validity is crucial as it directly influences fairness perceptions. Contingent on the testing structure and selection process, the feedback provided can be objective and quantitative information, including justifications for the selection decision and validity information. Previous research has shown that such feedback can positively impact the reactions of applicants (Bauer et al., 2011; Warszta, 2012).

Interestingly, participants in the study generally found AI use in S8 to be more valid than in S7. Participant 94, a recruiter, emphasized the AI's ability to be valid, stating,

"Generally happy with the process, especially those that involve AI using chatbots for how accurate they can be."

This positive perspective aligns with the potential benefits of AI in providing accurate and reliable assessments. In contrast, Participant 118, another recruiter, expressed skepticism about AI's accuracy and raised concerns about the organizational perception of using AI to cut labor costs. They stated,

"AI has been proven to make things up and not give answers that I would deem appropriate and reasonable."

Moreover, Participant 118 conveyed a lack of trust in companies that rely heavily on AI in the recruitment process, seeing it as an indication that higher-ups may not prioritize people. They articulated,

"I do not trust a company that removes people from the recruitment process and cuts labor costs with AI. It indicates to me that higher-ups likely do not care about people at all and would not want to work for them. AI is a tool to HELP people, not replace their roles."

This viewpoint emphasizes the importance of considering the ethical implications and organizational values when implementing AI in recruitment processes. Participants in the study indicated a positive perception of AI use in communication through chatbots, with non-significant differences in measures (S7, p=0.470, and S8, p=0.241). Importantly, this positive perception was not influenced by emotional creepiness.

Chatbots are viewed as a valuable assistant to recruiters, streamlining challenging and tedious tasks efficiently (Swapna & Arpana, 2021). Aligning with one of the responses received in the study, participant 123, a recruiter said,

“It should be used as a tool or an aid in the recruitment process.”

Chatbots are considered more objective and less susceptible to cognitive biases, thus reducing traditional human errors (Black & van Esch, 2020; Upadhyay & Khandelwal, 2018). Participant 18, an applicant, emphasized the benefit of AI's objectivity, stating,

"A pro is giving objective responses and answers."

Moreover, AI use in communication, particularly through chatbots, is seen as a means to enhance engagement. Chatbots can assist candidates by answering questions, providing information, and addressing any missing or unclear details for both hired and rejected candidates, a capability that surpasses what recruiters alone can offer (Nawaz & Gomes, 2020). This aligns with the overall positive acceptance of AI use in communication, in line with findings from previous studies (Dijkkamp, 2019; Laurim et al., 2021; Swapna & Arpana, 2021). Participants highlighted the usefulness of AI in communication, expressing positive sentiments. Participant 9, an applicant, specifically noted,

"I found it very useful for me as an applicant to be able to ask a chatbot some hard questions that I may be hesitant to ask a future employer (such as salary-related questions or certain questions related to work dress code or culture, etc.)."

This underscores the practical advantages and the role of chatbots in facilitating communication during the recruitment process.

Table 4.9: Mean and Standard Deviation (SD) Values of Measures Across AI Experts, Applicants, and Recruiters for Stage S7

	AI Expert		Applicant		Recruiter	
Survey Question	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
S7.1- Validity	3.26	1.15	3.21	1.02	3.35	0.98
S7.2- Satisfied	2.95	1.31	3.00	1.18	3.41	1.05
S7.3- Two-way communication	3.26	1.15	3.17	1.18	3.74	1.05
S7.4- Creepy	3.37	1.21	3.30	1.08	2.82	1.09
S7.5- organizational attractiveness	2.89	0.62	3.06	0.81	3.15	1.12
S7.6- privacy	2.95	1.18	3.70	1.03	3.24	1.05
S7.7 useful/benefit	3.53	1.02	3.24	1.18	3.50	1.29

Table 4.10: Mean and Standard Deviation (SD) Values of Measures Across AI Experts, Applicants, and Recruiters for Stage S8

Survey Question	AI Expert		Applicant		Recruiter	
	Mean	SD	Mean	SD	Mean	SD
S8.1- Satisfied	3.68	1.00	3.59	1.01	3.71	1.12
S8.2- Creepy	2.74	0.93	2.77	1.11	2.47	1.05
S8.3- Two-way communication	3.58	1.02	3.53	1.09	3.82	1.06
S8.4- Validity	3.37	1.07	3.47	0.99	3.38	1.04
S8.5- useful/benefit	3.47	1.12	3.31	1.15	3.70	1.02
S8.6-Organizational attractiveness	3.26	0.93	3.06	0.88	3.12	1.12
S8.7- Privacy	2.95	1.31	3.09	1.19	2.94	1.04

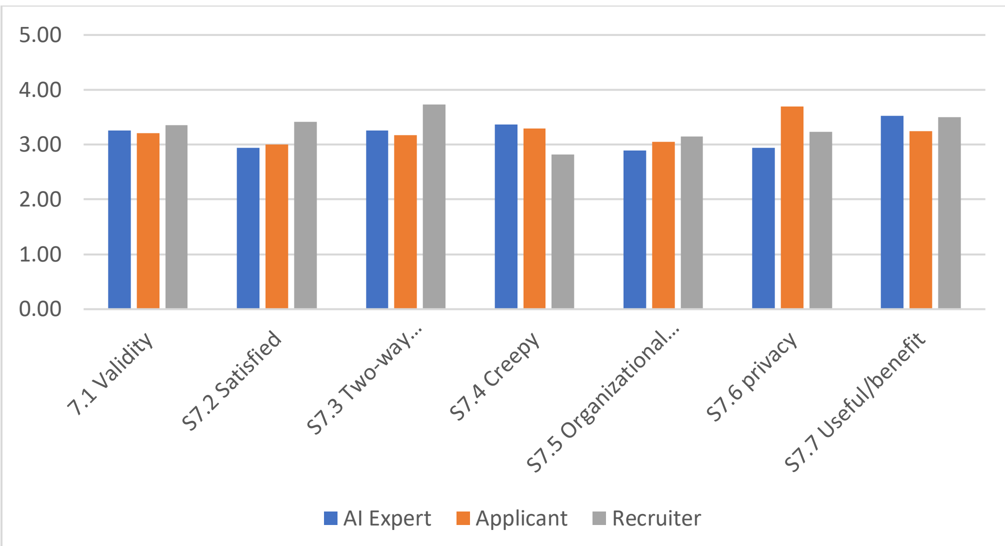

Figure 4.9: Perceptual Insights- Mean Values across S7.1 to S7.7 for AI Experts, Applicants, and Recruiters.

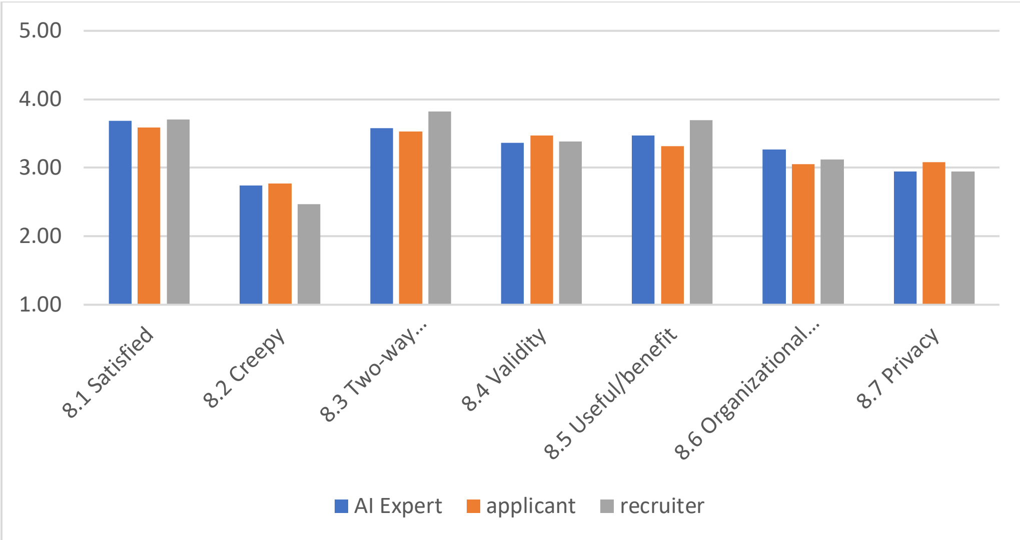

Figure 4.10: Perceptual Insights- Mean Values across S8.1 to S8.7 for AI Experts, Applicants, and Recruiters.

Chapter 5: Conclusion and Implications

Our primary objective in this thesis was to evaluate potential integration points of AI within the various stages of the recruitment process. Secondly, we focused on understanding the distinct perspectives held by AI experts, applicants, and recruiters concerning the utilization of AI at each phase of the recruitment journey. Lastly, we sought to discern whether divergences exist in these perceptions across the three stakeholder groups. As a crucial component of our investigation, we delved into the perceptions of fairness associated with the implementation of AI at specific stages of the recruitment process. By addressing these multifaceted aspects, our study aimed to contribute valuable insight into the nuanced dynamics and considerations surrounding the incorporation of AI in recruitment.

Our findings reveal that organizations leverage AI to enhance efficiency, reduce bias, save time and costs, and improve brand image, user experience, and engagement with passive job seekers (see Chapter 2 for RQ1). To answer RQ2, RQ3, and RQ4 (see Chapter 4), our participants completed a questionnaire that details eight distinct scenarios, encompassing the description, attraction, screening, assessment, and communication phases of AI recruitment. We used procedural justice measurements to analyze and collect the data. In the description phase (S1), participants exhibited positive perceptions, perceiving AI as fair, valid, and fostering positive organizational perceptions. Notably, recruiters found the use of AI less "creepy" compared to applicants and AI experts. Moving to the attraction phase (S2), positive organizational attractiveness, satisfaction, and fairness were evident, with moderate validity and minimal concerns about creepiness and privacy. The screening phase (S3) revealed positive organizational perceptions and neutral scores for the other measurements. AI experts perceived a higher chance to perform and lower creepiness perceptions than the other stakeholders. Recruiters found AI in S3 to be more valid. In the assessment phase, gamified assessments (S4) yielded neutral perceptions across several measures, with the notable observation that frequent video game players tended to exhibit more positive perceptions. Avatar interviews (S5) showcased higher perceptions of chance to perform among AI experts compared to applicants and recruiters, with an overall neutral mean perception of the other measures. There was a slight increase in creepiness and privacy concerns, but organizational perceptions were positive. In the selection phase (S6), participants demonstrated low fairness, validity, satisfaction, and trust perceptions, coupled with elevated concerns about privacy and creepiness. However, positive organizational attractiveness perceptions persisted. Communication is evaluated in scenarios discussing selection outcomes (S7) and through Q&A sessions (S8). S7 showed positive two-way communication, usefulness, and validity. Applicants had higher privacy concerns than recruiters and AI experts. S8 rendered positive scores for two-way communication, organizational attractiveness, satisfaction, usefulness, and validity with neutral privacy concerns and low creepiness perceptions. These nuanced findings highlight the complexity of integrating AI into recruitment processes, emphasizing the importance of considering diverse stakeholder perspectives.

The thesis' contribution lies in both the theoretical domain, where it extends existing knowledge, and the practical domain, where it explores the tangible impact of AI on the recruitment dynamics. Building on established recruitment models outlined in Chapter 1, this study adopts the traditional recruitment process by Holm (2012) as a foundation and integrates AI into each stage. Drawing examples from various sources, including Hunkenschroer & Luetge, (2022), the research not only identifies potential points of AI implementation but also underscores their relevance and applicability. An important finding of this thesis is the nuances in the perceptions held by recruiters, applicants, and AI experts. This research aligns with several psychological and ethical theories. Organizational justice theory explores perceptions of fairness in organizations, focusing on procedural justice (fairness of processes) and the idea of interactional justice (fairness of interpersonal treatment) (Colquitt, 2001). The study investigates how participants perceive the fairness of AI-driven recruitment processes, which relates directly to procedural justice.

It is evident that perceptions tend to be more positive for earlier scenarios of the hiring funnel. The empirical findings of this research hold significant implications for HR departments within organizations. They provide valuable insight that can guide recruiters and applicants alike in navigating the evolving landscape of recruitment, specifically with AI technologies. By understanding the nuances of perceptions and the impact at each stage, organizations can refine their strategies, fostering a more informed and efficient recruitment process.

This study fills a notable gap in the literature by investigating the reactions of AI experts and applicants to AI-driven recruitment decision-making processes. The study provides practical insights for Human Resource (HR) practitioners in designing recruitment strategies involving AI. It underscores the importance for organizations to actively address applicant concerns regarding comfort and privacy, particularly if they aim to attract top-tier candidates and prioritize a positive applicant experience (Chapman et al., 2005).

A prevailing sentiment expressed by participants emphasized the significance of human recruiters in establishing personal connections and fostering relationships between applicants and potential employers. Aligning with other research (Acikgoz et al., 2020; Mirowska et al., 2021; Noble et al., 2021; Warrenbrand, 2021), this underscores the recommendation for organizations considering AI implementation to integrate a human touch, as it was deemed valuable across participant groups, potentially alleviating negative perceptions related to fairness, creepiness, and other factors. This research contributes to the literature on human-automation interaction by examining the perceptions of recruiters, applicants, and AI experts regarding automated hiring processes. It sheds light on which stages of the process are perceived more favorably and the factors shaping these perceptions. The findings suggest that many participants advocate for a hybrid approach that combines automated recruitment processes with human involvement.

An intriguing observation emerged from the findings- despite concerns about privacy, lower fairness, and perceived creepiness, organizational attractiveness remained notably positive. Even with these reservations, potential applicants seemed undeterred, suggesting that the presence of AI did not negatively impact their willingness to accept a job offer. The implications of this thesis extend to organizations grappling with uncertainties about how applicants perceived the integration of AI. The research shows that applicants are generally open to undergoing a recruitment process with AI technology, providing valuable insight for organizations contemplating such implementations.

Furthermore, the thesis serves as a practical guide for organizations weighing the benefits and pitfalls of AI implementation and recruitment, as discussed in Chapter 2. The findings are generally supportive of the potential positive perceptions associated with the incorporation of AI within the recruitment process, which may allow organizations to capitalize on the advantages of the technology without incurring the risk of negative perceptions by stakeholders. Notably, AI experts viewed AI as a valid tool in certain scenarios (S1, S2, S7, and S8) but express reservation on others (S3, S4, S5, S6). This indicates a perceived limitation in the current capacity of AI to make final decisions particularly in emotional intelligent positions (S5 and S6). The results suggest a potential avenue for future research - exploring models for effective collaboration between humans and AI, with a focus on enhancing the decision-making process.

This research also addresses ethical theories related to privacy, data protection, and transparency which inform discussions about the responsible use of AI in recruitment. Organizations are urged to carefully consider the ethical implications of integrating AI into their recruitment processes. Algorithms trained on historical data have the potential to perpetuate or even exacerbate biases present in the data, posing challenges to how the public perceives algorithmic decision-making in hiring contexts (Tambe et al., 2019). Our study revealed that AI is not universally seen as bias-free, with some participants expressing concerns that biases could be coded into AI systems. Regardless of their role, participants emphasized the importance of collaborative decision-making, suggesting that reliance solely on AI may not be ideal.

One notable finding from our study is that applicants may lack sufficient information to gauge the fairness and validity of AI-driven recruitment procedures. Participants expressed skepticism about the accuracy and capacity of AI to predict performance accurately. Privacy emerged as a consistent concern across the scenarios, underscoring the need to address legal and regulatory considerations. Establishing compliance guidelines is crucial to ensuring that AI-based recruitment practices adhere to existing laws and regulations, thereby upholding ethical standards and fostering trust among participants and organizations.

Chapter 6: Limitations and Suggestion for Future Research

While the survey design aimed to capture diverse perspectives on AI in recruitment, this study presents certain limitations due to the self-reported nature of the data and potential response biases. The study primarily focused on AI perceptions and attitudes, lacking an exploration of qualitative factors or the impact of demographic variables (such as age, culture, etc.). A significant constraint lies in relying on hypothetical scenarios rather than real-life applicants (Hilliard et al., 2022), potentially limiting the understanding of actual intricacies in AI-based recruitment processes. Future research could benefit from concentrating on companies actively implementing AI in recruitment and obtaining direct feedback from applicants who have experienced these practices.

Another limitation is the narrow focus on the "how" of participants' feelings regarding AI in recruitment rather than delving into the "why." Future studies could explore applicants' past experiences with AI in recruitment to assess the impact of prior exposure on their perceptions. The role of direct involvement, especially from AI experts involved directly in developing or implementing AI systems for resume sorting, remains unexplored in this study. Investigating how this involvement influences their perceptions could yield valuable insights. Furthermore, we did not collect information regarding the size of the organizations the recruiters belong to. Recruiters from small, medium, or large enterprises may have different perspectives on the use of AI in recruitment. Additionally, we did not gather data on whether the recruiters' organizations are private or public entities. It would be valuable to explore whether recruiters' perceptions vary depending on the size and type of their organization and their level of involvement with it. For instance, investigating if there are differences in perceptions between those directly employed by the organization and those working as third-party recruiters could yield insightful findings. Understanding whether third-party recruiters prioritize fairness and the reputation of the organization, given their indirect involvement, would be particularly intriguing.

The temporal context of the study, conducted during a post COVID-19 recession, introduces a unique element that may impact participants' perspectives. Future research should reevaluate these perceptions under different economic conditions to ensure the robustness and relevance of the findings. The study lacks specific information on participants' professional involvement in AI implementation within the recruitment field, an aspect that could have influenced their perceptions. Additionally, once the application of AI becomes more prominent in the recruitment field, it would be interesting to examine which step of the recruitment process, or AI solution, are creating the most value for organizations and recruiters. Lastly, the use of a one-shot questionnaire methodology within a cross-sectional design raises concerns about common-method variance and limits the extent of casual interpretations, as noted by Nikolaou & Georgiou (2018). These methodological considerations underscore the need for caution in attributing casualty based solely on the study's design. The thesis provided insights into the perspectives of AI experts, applicants, and recruiters, highlighting the distinctions among their perceptions. Future studies could replicate the same scenarios, comparing two conditions- one utilizing AI and another without- and assess participants' preferences for human recruiters versus AI recruiters within analogous settings. This approach would further illuminate the nuanced dynamics between human and AI involvement in the recruitment process.

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Appendix A: Survey Related Information

Table 7.1 Survey scale items and their source

Scale	*Items*	*Source*
Perceived Fairness	I believe that this procedure to write the job description was fair.	*Chan et al. (1998)*
	All things considered this selection procedure was fair.	*Warszta (2012)*
	The use of the test would allow screening every applicant fairly and giving them the same opportunity to compete for the job.	*Chan et al.* (1998)
	I think this interview is a fair procedure to select people for the job.	*Warszta (2012)*
Chance to Perform	The applicant could really show their skills and abilities through this process	*Bauer et al. (2001), Warszta (2012)*
Predictive validity/accuracy	I am confident that AI developed a correct job description based on the information provided.	*Chan et al. (1998)*
	I am confident that ATS can predict how well an applicant will perform on the job.	*Chan et al. (1998)*
	The employer can tell a lot about the applicant's ability to do the job based on the results of the test.	*Chan et al. (1998)*
	Failing to perform well on the test indicates that the applicant cannot perform well on the job.	*Chan et al.* (1998)
	I trust that the information provided by the chatbot is true and accurate.	*Self-developed*
Satisfaction	Overall, I was satisfied with this job description development process.	*Sylva and Mol's (2009)*
	Overall, I was satisfied with this recruitment process.	*Sylva and Mol's (2009)*
	Overall, I was satisfied with this application process.	*Sylva and Mol's (2009)*
Emotional Creepiness	During this situation, I had a queasy feeling.	*Langer and König (2017)*
	I had a feeling that there was something shady about this situation.	*Langer and König (2017)*
	This situation somehow felt threatening.	*Langer and König (2017)*
	I felt uneasy during this situation.	*Langer and König (2017)*
Creepy ambiguity	I did not know how to judge this situation.	*Langer and König (2017)*
	During this situation, things were going on that I did not understand.	*Langer and König (2017)*
	I did not know exactly how to behave in this situation.	

	I did not know exactly what to expect of this situation	*Langer and König (2017)* *Langer and König (2017)*
Overall organizational Attractiveness	I am interested in learning more about this company. there are probably many who would like to work at this company. I would recommend others to apply to this company. If this company invited me for a job interview, I would go. I would accept a job offer from this company. This is a reputable company to work for This company probably has a reputation as being an excellent employer	*Langer et al. (2021)* *Langer et al. (2021)* *Langer et al. (2021)* *Langer et al. (2021)* *Langer et al. (2021)* *Langer et al.* (2021) *Langer et al. (2021)*
Privacy	Situations like the one shown threaten my privacy. Novel technologies are threatening privacy increasingly. I am concerned that companies are collecting too much personal information about me. situations like this one, I am concerned about my privacy. Private data that are provided in such situations could be misused. I am concerned about my privacy.	*Langer et al. (2021), modified* *Langer et al. (2021)* *Langer et al. (2021)* *Langer et al. (2021)* *Langer et al. (2021)* *Malhotra et al.* (2004)
Usefulness/ benefit	The mode of communication benefits me, the applicant. Feedback and communication from the chatbot will help with my personal and professional development.	*Self-developed* *Self-developed*
Two-way communication	I would have felt comfortable asking questions, if I had any	*Bauer et al. (2001), Warszta (2012)*

Table 7.2 Survey scenario descriptions as listed in the survey.

Scenario Number	**Scenario description (as stated in survey)**
S1	Imagine that you are searching to apply for a position. You found out that Company A has posted a job that exactly matches your skills and expectations for a position in your desired industry. The job advertisement for the role at Company A tells you that AI was used to write, edit, and upload the posting. The posting was developed by AI through analyzing and comparing the previous descriptions to the current work being performed as well as by analyzing what the people in the current role do.

S2	Imagine that you are searching for a job using multiple online platforms (ex. Indeed, social networking sites, and LinkedIn). While on these platforms, you receive an advertisement for a role at Company B that exactly matches your skills and expectations for a position in your desired industry. The advertisement notifies you that an applicant tracking system (ATS) was used to find you this job match. ATS are installed with artificial intelligence and machine learning in order to find an ideal candidate based on information from their resumes, and other roles they have applied to.
S3	Imagine that you apply to a position that you are very interested in at Company C. You are asked to upload your resume on the company's website. The website informs you that your resume will be screened using artificial intelligence software. This software evaluates your qualifications and compares your resume to other applicants for the position using an advanced algorithm. It assigns each applicant an automated score based on the content of their resume and how it compares with the qualifications of current employees who have been successful in those roles. Only resumes with a certain score are sent to hiring managers for further review.
S4	After submitting your resume, you received an automated notification/ email inviting you to participate in an AI driven gamified assessment test. The assessment consists of 3 online games that take a total of 15 minutes to complete all of them. These games are simple task games that measure your soft skills based on performance on the test (ie. Leadership traits, design thinking, empathy etc.). The games used are dependent on what information the vacant role requires. An example of a game would be remembering 4 digits that are shown on the screen for a short period of time, a simple card game or a basic video game simulator. The AI software compares the candidates' results to successful workers in the current job position. If applicants succeed in matching requirements that the company expects they may be scheduled for an interview. The requirements are not explicitly stated.
S5	After completing your assessment, you received an automated notification/ email inviting you to participate in an automated video interview run by AI. You receive a link that is available 24/7 (ie. Any day and anytime within the given time frame). The interview must be completed within 10 days of receiving the link. The link leads you to set up for a virtual interview using a webcam and microphone on your computer with AI software showing the interviewer as an avatar. The avatar analyzes facial expressions by recognizing eye movement eye contact and facial movements (ex. Smiling), as well analyzes your gestures specifically hand body and head movements (ex. Nodding), along with speech and voice recognition including pitch volume pauses that infer on personality traits like extraversion or introversion. The AI-enabled avatar proceeds to ask you various structured interview questions. An example of such question "tell me your greatness weakness". Your responses are both audio and video recorded on the computer, the contents of your response

	along with verbal and nonverbal communications are analyzed by the AI software. The software matches your responses with the characteristics and behaviors of successful employees. You, the candidate, are then given an automated score that helps the company decide whether you are a good hire or not.
S6	After completing your gamified assessment test and virtual assisted interview, you receive a score. An AI machine learning software tallies the scores of your gamified assessment test, video interview, and information provided on your resume to provide a final score. The final score is then compared to other candidates, the candidate with the best match for the job will receive an offer based on the data-driven decision-making process of the AI software.
S7	Suppose you have applied for a role at Company E. You have already submitted your resume, completed assessments and have gone through the interview process. You are now waiting for the final decision on whether you were accepted for the role. You receive an email along with a link. The link provides you access to an automated chatbot who provides information and explains your strengths in your interview and assessment test. Along with providing you feedback as to why you were or weren't selected for the role.
S8	Suppose you are interested in applying to Company D. The job description is vague, and you have questions regarding the role, the pay, the benefits of the position, and the nest steps in the application process. You want to gain more information about the role but are not sure whom to contact. The job listing at Company D informs you that there is a chatbot that can be used to answer general questions, FAQs, policies, culture etc. As well, it has the ability to schedule interviews based on your availability. Chatbots enable real-time communication with candidates through email, personal messaging, or dialogue box on company's website. You have concerns about the pay range for the position, you proceed to ask the chatbot what the current salary for the position is. The chatbot goes through Company D's database and lists the previous salaries for the role. Along with any other questions you may have concerning the job or the application process. Likewise, it is able to ask you questions to see if your experience matches the job expectations and requirements. You are able to use this chatbot throughout the recruitment process to answer any questions or concerns you may have.

Table 7.3. Demographic questions

Question code and description	Question as stated in survey
D1-Experimentation Propensity	[If I heard about a new information technology, I would look for ways to experiment with it.]
D2- Early Adoption Tendency	[Among my peers, I am usually the first to try out new information technologies]
D3- Hesitancy towards New Technologies	[In general, I am hesitant to try out new information technologies]
D4- Confidence in AI Decision-Making	[I am confident with the decision-making process of artificial intelligence assisted technology]
D5- Confidence in AI Data Analysis	[I am confident with the information output made by artificial intelligence through analyzing large volumes of documents to summarize texts.]
D6- Confidence in AI for Personalized Decisions:	[I am confident with the results of using artificial intelligence to make decisions on what to cook based on the ingredient list provided and knowing food preferences was given.]
D7- preference for AI in Routine Transactions	[For routine transactions, I would rather interact with an artificially intelligent system than with a human]
D8- Familiarity with the Term "Artificial Intelligence"	[I am familiar are you with the term artificial intelligence technology?]
D9 Knowledge of AI Applications	In your opinion, which of the following technologies, if any, uses artificial intelligence (AI)?

Table 7.4: Mean values and standard deviation for Demographic questions based on participant role.

Demographic Question	AI expert		Applicant		Recruiter	
	Mean	SD	Mean	SD	Mean	SD
D1	4.58	0.69	3.985714286	0.77	4.058823529	0.814310509
D2	3.89	0.66	3.371428571	0.68	3.617647059	0.985184366
D3	2.42	0.96123702	2.385714286	0.96	1.941176471	0.814310509
D4	3.79	0.713282504	3.17	0.90	3.44	0.959519339
D5	3.68	0.749268649	3.557142857	1.001964943	3.705882353	0.871411664
D6	3.79	0.787326515	3.642857143	0.901459594	3.647058824	0.98110491
D7	4.03	1.261207071	3.157142857	1.071849469	3.617647059	1.101368457

D8	0.89	0.696692268	4.371428571	0.725746564	4.411764706	0.701411869
D9	0.89	0.315301768	0.8	0.402888124	0.647058824	0.48507125

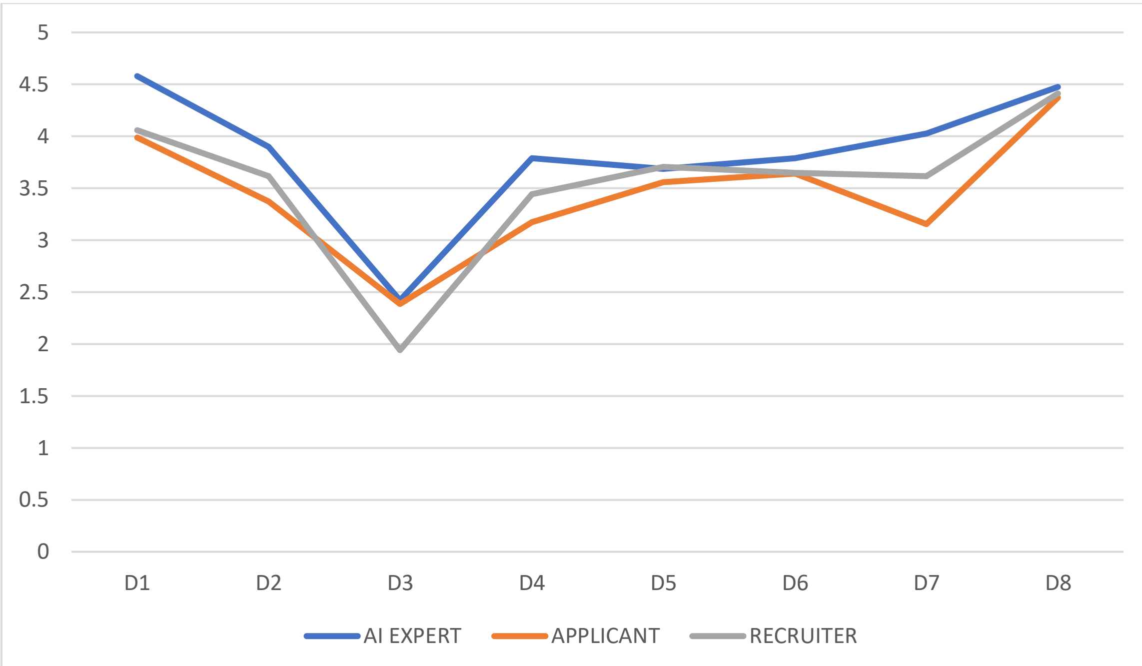

Figure 7.1: Trend of participants demographic question responses towards general application of AI

Appendix B: ANOVA Tables for each Scenario

Table 7.5 ANOVA results for S1.

			Sum of Squares	df	Mean Square	F	Sig.
S1.2 Fair	Between Groups	(Combined)	.457	2	.229	.302	.740
	Within Groups		91.006	120	.758		
	Total		91.463	122			
S1.4 Validity	Between Groups	(Combined)	.128	2	.064	.086	.918
	Within Groups		89.839	120	.749		
	Total		89.967	122			
S1.3 Satisfied	Between Groups	(Combined)	.433	2	.216	.316	.730
	Within Groups		82.250	120	.685		
	Total		82.683	122			
S1.5 Creepy	Between Groups	(Combined)	11.645	2	5.823	5.497	.005
	Within Groups		127.103	120	1.059		
	Total		138.748	122			
S1.1 organization	Between Groups	(Combined)	.019	2	.010	.013	.987
	Within Groups		87.168	120	.726		
	Total		87.187	122			

Table 7.6 ANOVA results for S2

			Sum of Squares	df	Mean Square	F	Sig.
S2.1 organization	Between Groups	(Combined)	.208	2	.104	.249	.780
	Within Groups		50.133	120	.418		
	Total		50.341	122			

S2.2 Satisfied	Between Groups (Combined)	.435	2	.218	.339	.713
	Within Groups	77.028	120	.642		
	Total	77.463	122			
S2.3 Fair	Between Groups (Combined)	1.419	2	.710	.859	.426
	Within Groups	99.085	120	.826		
	Total	100.504	122			
S2.4 Validity	Between Groups (Combined)	5.728	2	2.864	2.459	.090
	Within Groups	139.752	120	1.165		
	Total	145.480	122			
S2.5 Creepy	Between Groups (Combined)	1.137	2	.568	.537	.586
	Within Groups	127.026	120	1.059		
	Total	128.163	122			
S2.6 Privacy	Between Groups (Combined)	2.048	2	1.024	.740	.479
	Within Groups	166.115	120	1.384		
	Total	168.163	122			

Table 7.7 ANOVA results for S3

			Sum of Squares	df	Mean Square	F	Sig.
S3.5 Creepy	Between Groups	(Combined)	8.514	2	4.257	3.404	.036
	Within Groups		150.088	120	1.251		
	Total		158.602	122			
S3.1 Fair	Between Groups	(Combined)	4.774	2	2.387	2.001	.140
	Within Groups		143.193	120	1.193		
	Total		147.967	122			
S3.2 Chance to perform	Between Groups	(Combined)	9.338	2	4.669	3.782	.026
	Within Groups		148.125	120	1.234		
	Total		157.463	122			
S3.3 Validity	Between Groups	(Combined)	9.025	2	4.513	3.839	.024
	Within Groups		141.040	120	1.175		
	Total		150.065	122			
S3.4 Satisfied	Between Groups	(Combined)	6.161	2	3.080	2.694	.072
	Within Groups		137.205	120	1.143		
	Total		143.366	122			
S3.6 Organization	Between Groups	(Combined)	2.946	2	1.473	1.541	.218
	Within Groups		114.713	120	.956		
	Total		117.659	122			
S3.7 Privacy	Between Groups	(Combined)	1.007	2	.503	.394	.675
	Within Groups		153.400	120	1.278		
	Total		154.407	122			

Table 7.8 ANOVA results for S4

			Sum of Squares	df	Mean Square	F	Sig.
S4.1 Fair	Between Groups	(Combined)	.467	2	.234	.175	.840
	Within Groups		160.525	120	1.338		
	Total		160.992	122			
S4.3 Validity	Between Groups	(Combined)	1.742	2	.871	.757	.471
	Within Groups		138.112	120	1.151		
	Total		139.854	122			
S4.2 Chance to perform	Between Groups	(Combined)	.689	2	.344	.279	.757
	Within Groups		148.141	120	1.235		
	Total		148.829	122			
S4.4 Satisfied	Between Groups	(Combined)	2.693	2	1.346	1.056	.351
	Within Groups		153.014	120	1.275		
	Total		155.707	122			
S4.5 Creepy	Between Groups	(Combined)	1.419	2	.710	.534	.587
	Within Groups		159.378	120	1.328		
	Total		160.797	122			
S4.6 Orgnization	Between Groups	(Combined)	1.506	2	.753	.699	.499
	Within Groups		129.291	120	1.077		
	Total		130.797	122			
S4.7 Privacy	Between Groups	(Combined)	3.216	2	1.608	1.306	.275
	Within Groups		147.711	120	1.231		
	Total		150.927	122			

Table 7.9 ANOVA results for S5

			Sum of Squares	df	Mean Square	F	Sig.
S5.1 Fair	Between Groups	(Combined)	3.609	2	1.805	1.196	.306
	Within Groups		181.074	120	1.509		
	Total		184.683	122			
S5,2 Chace to perform	Between Groups	(Combined)	9.658	2	4.829	3.439	.035
	Within Groups		168.505	120	1.404		
	Total		178.163	122			
S5.3 Validity	Between Groups	(Combined)	1.927	2	.964	.682	.508
	Within Groups		169.536	120	1.413		
	Total		171.463	122			
S5.4 Satisfied	Between Groups	(Combined)	4.922	2	2.461	1.589	.208
	Within Groups		185.874	120	1.549		
	Total		190.797	122			
S5.5 Creepy	Between Groups	(Combined)	2.304	2	1.152	.714	.492
	Within Groups		193.761	120	1.615		
	Total		196.065	122			
S5.6 Organization	Between Groups	(Combined)	3.725	2	1.862	1.226	.297
	Within Groups		182.340	120	1.520		
	Total		186.065	122			
S5.7 Privacy	Between Groups	(Combined)	.949	2	.475	.290	.749
	Within Groups		196.368	120	1.636		
	Total		197.317	122			

Table 7.10 ANOVA results for S6

		Sum of Squares	df	Mean Square	F	Sig.
S6.1 Fair	Between Groups (Combined)	1.573	2	.787	.587	.558
	Within Groups	160.768	120	1.340		
	Total	162.341	122			
S6.2 Validity	Between Groups (Combined)	2.252	2	1.126	.936	.395
	Within Groups	144.399	120	1.203		
	Total	146.650	122			
S6.3 Satisfied	Between Groups (Combined)	.170	2	.085	.067	.936
	Within Groups	153.748	120	1.281		
	Total	153.919	122			
S6.4 Creepy	Between Groups (Combined)	2.015	2	1.008	.773	.464
	Within Groups	156.326	120	1.303		
	Total	158.341	122			
S6.5 Organization	Between Groups (Combined)	.316	2	.158	.145	.866
	Within Groups	131.164	120	1.093		
	Total	131.480	122			
S6.6 Privacy	Between Groups (Combined)	6.877	2	3.438	3.020	.053
	Within Groups	136.603	120	1.138		
	Total	143.480	122			

Table 7.11 ANOVA results for S7

			Sum of Squares	df	Mean Square	F	Sig.
S7.1 Validity	Between Groups	(Combined)	.440	2	.220	.208	.813
	Within Groups		127.235	120	1.060		
	Total		127.675	122			
S7.2 Satisfied	Between Groups	(Combined)	4.443	2	2.222	1.634	.200
	Within Groups		163.183	120	1.360		
	Total		167.626	122			
S7.3 Two-way communication	Between Groups	(Combined)	7.414	2	3.707	2.847	.062
	Within Groups		156.245	120	1.302		
	Total		163.659	122			
S7.4 Creepy	Between Groups	(Combined)	6.003	2	3.001	2.466	.089
	Within Groups		146.062	120	1.217		
	Total		152.065	122			
S7.5 Organization	Between Groups	(Combined)	.518	2	.259	.330	.719
	Within Groups		94.084	120	.784		
	Total		94.602	122			
S7.6 Privacy	Between Groups	(Combined)	10.739	2	5.370	4.817	.010
	Within Groups		133.765	120	1.115		
	Total		144.504	122			
S7.7 useful/benefit	Between Groups	(Combined)	2.152	2	1.076	.759	.470
	Within Groups		170.108	120	1.418		
	Total		172.260	122			

Table 7.12 ANOVA results for S8

			Sum of Squares	df	Mean Square	F	Sig.
S8.1 Satisfied	Between Groups	(Combined)	.387	2	.193	.178	.837
	Within Groups		130.150	120	1.085		
	Total		130.537	122			
S8.2 Creepy	Between Groups	(Combined)	2.136	2	1.068	.939	.394
	Within Groups		136.498	120	1.137		
	Total		138.634	122			
S8.3 2-way Communication	Between Groups	(Combined)	2.025	2	1.013	.887	.415
	Within Groups		137.016	120	1.142		
	Total		139.041	122			
S8.4 Validity	Between Groups	(Combined)	.269	2	.135	.130	.878
	Within Groups		123.893	120	1.032		
	Total		124.163	122			
S8.5 Useful/ benefit	Between Groups	(Combined)	3.525	2	1.763	1.440	.241
	Within Groups		146.881	120	1.224		
	Total		150.407	122			
S8.6 Organization	Between Groups	(Combined)	.641	2	.320	.347	.708
	Within Groups		110.985	120	.925		
	Total		111.626	122			
S8.7 Privacy	Between Groups	(Combined)	.611	2	.306	.223	.800
	Within Groups		164.315	120	1.369		
	Total		164.927	122			